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Agricultural Productivity and the Fight Against Deforestation

An Empirical Analysis of the Effect of Factor-Biased Technical Change on Agricultural Land Use and Forests in Brazil

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Abstract

The aim of this thesis is to study the effect of two new agricultural technologies on agricultural land use and forests. To guide our empirical work, we present a simple model in which the effect on land use in agriculture depends on the factor-bias of technical change. To test the predictions of the model, we utilize an instrumental variables approach to study the introduction of genetically engineered soy and a second harvesting season of maize in Brazil. In order to identify the effect of these technologies, we exploit the exogenous timing of their adoption, in addition to their heterogeneous impacts on agricultural productivity across geographical areas.

Our main finding is that technical change in agriculture has ambiguous effects on forest loss. First, land-augmenting technical change, in the form of second season maize, increases the land productivity which reduces pressure on forests. Second, labor-augmenting technical change, in the form of genetically engineered soy, increases labor productivity, rising the pressure on forest. However, our results suggest that a second harvesting season of maize primarily is exploited as a method to consolidate soy and maize cultivation. Thus, we find the effect of land augmenting technical change to be indirect, as a result of increased double cropping of soy and maize leading to a reduction in first season maize cultivation. We also find indications of genetically engineered soy replacing cultivation of first season maize.

Acronyms

2SLS	Two-Stage Least Square
AEZ	Agro-Ecological Zones
CONAB	Companhia Nacional de Abastecimento
FAO	Food and Agriculture Organization of the United Nations
GAEZ	Global Agro-Ecological Zones
GDP	Gross Domestic Product
GE	Genetically Engineered
IBGE	Instituto Brasiliero de Geografia e Estatística
IIASA	International Institute for Applied Systems Analysis
IV	Instrumental Variables
NGO	Non-Governmental Organization
OLS	Ordinary Least Squares
OVB	Omitted Variable Bias
PAM	Produção Agrícola Municipal
PPCDA	Action Plan for the Prevention and Control of Deforestation in the Legal Amazon
UNFCCC	United Nations Framework Convention on Climate Change
USDA	United States Department of Agriculture
USDA FAS	USDA Foreign Agriculture Service

Important Concepts

Factor-Biased Technical Change: A shift in the production technology that favors one factor, over the other factor, by increasing its relative productivity and, therefore, its relative demand.

Land-Augmenting Technical Change: A technology which makes land relatively more productive.

Labor-Augmenting Technical Change: A technology which makes labor relatively more productive.

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1 Introduction

Tropical forests play a crucial role in human existence. Despite this fact, depletion of forests has increased over the decades, with agricultural production as one of the key drivers (Benhin, 2006). According to population projections, the world population will reach nearly 11 billion by 2100 (United Nations, 2017). Thus, a key question is how the humankind will manage to meet the requirement of a doubling in food production, without causing serious harm to the world's ecosystems (Tilman, 1999). In answering this question, agricultural productivity plays an important part.

Basic economic theory implies that all changes making agricultural production more profitable should stimulate land expansion, possibly inducing deforestation (Angelsen & Kaimowitz, 2001). However, agriculture technologies also increase total production on existing agricultural land area, leading to less need for land. Thus, it seems evident that an intensification of agricultural production can have the potential to increase food production without increasing the pressure on forests. Regardless of a relatively large amount of theoretical literature discussing these effects, the empirical evidence testing the mechanisms proposed by these models are scarce[1].

In this thesis we provide empirical evidence of the effect of increased agriculture productivity on agricultural land use and forests in Brazil. We study the effect of the adoption of two new agricultural technologies; genetically engineered soy seeds (GE soy) and a second harvesting season in maize. We argue that GE soy can be defined as labor-augmenting technical change, due to he fact that these seeds requires less labor per unit of land to yield the same out. In the case of a second harvesting season of maize, we argue that this technology can be defined land-augmenting, because the technique effectively increases land endowment. The simultaneous expansion of these two crops, and their different impact across Brazil, constitutes a natural experiment which enables us to investigate the effect of different types of technologies on agricultural land use and forests.

Our estimation strategy is an instrumental variables (IV) approach, inspired by Bustos at al. (2016) and their paper *Agricultural Productivity and Structural Transformation*. Similarly to Bustos et al. (2016) our estimation strategy is based on a reduced form estimation. However, in our analysis, we also conduct a two-stage least squares (2SLS) estimation. The main motivation behind including a 2SLS regression is to examine the mechanisms driving our results from the reduced form estimates.

To guide our empirical work, we present a simple model which illustrates the effect of

[1]Studies include Angelsen & Kaimowitz (2001), Larson (1991), Nghiep (1979), Holden (1993), Hornebeck & Keskin (2014), Severnini (2014), and Assunção et al. (2016).

factor-biased technical change on factor demand. The model is a continuation of the model and findings presented by Bustos et al. (2016), and forms the basis of the two predictions tested in this thesis. First, the model predicts that land-augmenting technical change effectively increases the land endowment which reduces the need for land in agricultural production. Consequently, this type of technical change has the potential to reduce pressure on forests. Second, labor-augmenting technical change makes each worker more productive, leading to increased demand for land in agricultural production. Thus, this type of technological change increases the pressure on forests. Taken together, the model predicts that the effect of increased agricultural productivity on agricultural land use and forests depends on the factor-bias of technical change.

We take advantage of newly developed, detailed, municipality-level data on land cover and land transition, for the whole of Brazil. The data is developed by the MapBiomas project (2018b), and was released September 2018. More specifically, we exploit the data to construct four outcome variables measuring different types of land use; *Forest cover*, *Agricultural land cover*, *Transition of land from forest to agriculture* and *Transition of land from agriculture to forest*. Our full dataset is constructed by linking these variables, with data assembled by Bustos et al.(2016) from the Brazilian Agricultural Census (IBGE, 1996, 2006) and FAO (2018b). Moreover, we have supplement the dataset with additional data obtained from the Brazilian Agricultural Census (1996, 2006) and the Produção Agrícola Municipal (PAM) database (2016). In the empirical analysis we utilize data from the last two rounds of the agricultural census.

When a new technology becomes available, it is not necessarily randomly adopted across space or time (Beaudry, Doms, & Lewis, 2010). Instead, research demonstrates that it is adopted only in environments in which complementary factors are cheap and available (Zeira, 1998; Basu & Weil, 1998; Beaudry & Green, 2005). Consequently, endogeneity is likely to be a problem when studying technology adoption, and an instrument can be necessary (Beaudry et al., 2010). In this thesis we use estimates of change in potential yields of soy and maize under different inputs across geographical areas of Brazil, as instruments for the endogenous variables of expansion in areas cultivated with GE soy and second season maize. The variables are functions of weather and soil characteristics, and not of actual yields in Brazil. Hence, we argue that they can be used as a source of exogenous variation in agricultural productivity across geographical areas.

We begin our analysis by conducting a reduced form estimation. In this part of the analysis we find evidence that land-augmenting technical change decreases the need for land in agricultural activities, reducing pressure on forest. In addition, our results suggest that labor-augmenting technical change increases the need for land in agricultural activities, boosting deforestation. Interestingly, our reduced form estimates further indicate that land-augmenting technical change can induce regrowth of forests.

In the second part of the analysis we estimate the IV regressions. The estimations provide us with interesting and complex information. Foremost, we find evidence that the two agricultural technologies do not expand interdependently from each other. More precisely, we find that the technique of a second harvesting season in maize primarily expands into areas highly suited for soy cultivation. These results indicate that second season maize is used as a way of jointly cultivating soy and maize, rather than as a method for double cropping two consecutive seasons of maize. Consequently, our results suggest that the estimated effects of land-augmenting technical change, found in the reduced form regressions, mainly originates from a decline in the cultivation of first season maize, and not directly through an expansion in second season maize. Moreover, we find evidence that GE soy expands in areas suited for both maize and soy, being an indication of GE soy expanding into the areas formerly cultivated with first season maize. These results suggest that the estimated effects of labor-augmenting technical change, found in the reduced form regressions, mainly occurs through increased co-cultivation of GE soy and second season maize. In addition, we find evidence of this effect being accompanied by GE soy also expanding into areas traditionally cultivated first season maize. These findings are in contrast to the findings of Bustos et al. (2016), who base their empirical analysis on the assumption that potential yields can be used as a predictor of crop specific technical change.

In sum, our results suggest that the factor-bias of technical change can be a key determinant of the relationship between agricultural productivity and deforestation. Land-augmenting technical change, in the case of second season maize, leads to a reallocation of maize cultivation, reducing the pressure on forests. In contrast, labor-augmenting technical change, in the case of GE soy, causes agriculture to expand both in areas of traditional soy cultivation and in new areas, previously cultivated with maize. Consequently, this technology increases the pressure on forests.

The topic studied is of particular interest due to several reasons. First, previous research indicate that increasing productivity in agriculture can have ambiguous effects on use of land. Thus, investigations with regard to different types of technologies can give insight into the potential effects of technical progress in agriculture. Second, providing a stable and efficient way to sustain enough crops to feed the growing world population, without causing serious harm to forest, is one of the main goals of technological development in agriculture (Cropper & Griffiths, 1994; Assuncao, Lipscomb, Mobarak, & Szerman, 2016). Hence, greater knowledge of the link between agriculture productivity and land use can have implications for current policies. Last, because global deforestation is the source of nearly 20% of total greenhouse gas emissions (Stern, 2008), the Norwegian Government contributes significantly to the Amazon Fund (Norwegian Ministry of Climate and Environment, 2018; The Amazon Fund, 2018). Thus, a better understanding of how technological change in agriculture affects land use, will accordingly contribute to guide future investments in actions which aims to reduce deforestation.

The remainder of the thesis continues as follows. In Section 2, we provide a review of the previous literature. We present background information on forest and agricultural land use, as well as the two technological changes in soy and maize, in Section 3. In Section 4 we outline a simple economic model forming the bases of our predictions. We describe our data in Section 5, followed by an overview of our empirical strategy in Section 6. Section 7 presents our analysis and our results, with a discussion of possible shortcomings in Section 8. Lastly, we conclude in Section 9.

2 Related Literature

In the following subsections, we review studies that analyze the different topics of interest, and discuss how our thesis contributes to the existing literature.

2.1 Deforestation, Agricultural Productivity & Land Use

Despite the vast amount of literature studying either the effects of agricultural productivity or land use and deforestation, the amount of literature studying the links between these two are more scarce. With regard to deforestation, studies have largely been focused on the Amazon forest, and few include forest and agricultural land cover for the whole of Brazil. Andersen et al. (2002) investigate forest dynamics and economic growth, in order to understand the value of preserving remaining forest. Moreover, other studies on deforestation in the Amazon forest include, but are not limited to, Achard et al. (2002), Moran (1993), Nelson et al. (1986), Nepestad et al. (2009) and Tyukavina et al. (2017). Increased attention has also been drawn to other biomes. One example is Kastnes at al. (2017), who study the impacts of th soy moratorium on soybean and deforestation dynamics in Mato Grosso. In contrast to the studies mentioned above, this thesis considers all municipalities across Brazil, and accordingly all Brazilian biomes.

Studies on change in land use include Hungthon (1994) and Foley et al. (2005), who emphasize how effects of change in land use has become a global topic of interest during the last decades. Further, Lambin et al. (2003) highlight the complexity of change in land cover and land use. Change in land use, especially in relation to farming purposes, is often looked into alongside deforestation. One example is studies which look into the relationship between land used for pasture and agricultural crops and loss of forest cover in Amazonia. Among those are Saatchi et al. (1997), Tyukavina et al. (2017) and Verburg et al. (2014). The latter find that an increase in commodity prices of beef and soy strongly increase deforestation. They highlight that tight conservation policies can reduce deforestation rate without a notable reduction in agricultural production. Similarly, Tyukavina et al. (2017) argue that 63% of total area of lost forest cover in Legal Amazon is linked to agroindustrial clearing for pasture and, 9% agroindustrial clearing for cropland.

The research linking use of land to agricultural technology is limited. Through the use of a theoretical conceptual model, Larson (1991) finds the effect of technological improvements on deforestation to be indeterminate. Moreover, Nghiep (1979) and Holden (1993) both find that technologies which increases the profitability of more intensive production systems reduce the need for clearing additional forests for agricultural land. Hornebeck & Keskin (2014) investigate the effect of use of irrigation technology, and find that groundwater access increases agricultural land values and initially reduces the impact of drought. Lewis and Severnini (2014) study the effect of electricity on agriculture in the United States. Their results suggests that rural electrification leads to large gains in agricultural employment and farm population.

Our paper is closely linked to Assunção et al. (2016), who study the effects of agriculture technology on forest cover through the expansion of rural electrification in Brazil during 1960-2000. Their analysis is based on the theory that increased agricultural productivity can, on one side, expand the scope of farming, but, on the other, side also intensify production. They use state-level data from five Brazilian Agricultural Censuses, and their results suggest that electrification increased crop productivity and caused farmers to expand production. With regard to forest loss, the authors find the effect to be ambiguous. They argue that for the typical state in their sample, a 10% increase in electricity infrastructure causes native vegetation to increase by -0.18% to 2.7%, whereby the magnitude of the effect depends on the prior state of native vegetation outside the farms.

In addition, our thesis relates closest to Bustos et al. (2016), who study the effects of the adoption of new agricultural technologies on structural transformation. In an effort to establish a causal relationship between agricultural productivity and structural transformation, they exploit two sources of exogenous variation in the profitability of technology adoption. More specifically, they study the effect of adoption of GE soy and second harvesting season of maize. The authors find evidence that labor-augmenting technical change in agriculture can encourage industrialization. Further, their results imply that land-augmenting technical change in agriculture can hamper industrialization. When developing the model guiding our predictions we build on these empirical evidences. In addition, because of the similarity with regard to data and methodology, we will refer to Bustos et al. (2016) throughout this thesis.

2.2 Implications for our Study

Our paper contributes to the existing literature in various areas. First, to the best of our knowledge, this is the first study of its kind to exploit data on land use for the whole of Brazil. The latest MapBiomas datasets were published in September 2018, updated with data dating back to 1985, covering all Brazilian municipalities. Thus, we expect to find results not directly comparable to the results of previous studies, as these mainly focus on the Amazonia biome. Second, our study is among few to link the effect of technological change in agriculture to change in land use, exploiting empirical data. Lastly, we contribute to existing literature by studying two types of technical change, one land-augmenting and one labor-augmenting, providing interesting information about the potential effects on land use, related to each of them.

3 Background

The Brazilian agricultural sector has developed considerable during the last decades, which as has been reflected in increased deforestation (Assuncao et al., 2016). In the following section we will look at historical development in forest and agricultural land use. We also present background information regarding the two technological changes of interest in this thesis.

3.1 Forests and Agricultural Land Use

3.1.1 Global Deforestation

Researchers have estimated that the forests that once covered the earth in total amounted to around six billion hectares (Bryant, Nielson, & Tangley, 1997). Today, only around 3.7 billion hectares of forest remain, according to the latest Global Forest Resources Assessment published by Food and Agriculture Organization of the United Nations (FAO) (FAO, 2016).

Deforestation is defined as the conversion from forest to non-forest lands (Achard et al., 2002). Consequently, this definition hinges on what is considered to be a forest. The United Nations Framework Convention on Climate Change (UNFCCC) defines forest as having at least 10% cover (Sasaki & Putz, 2009). By this definition the central Brazilian Savanna (cerrado) is considered to be forest, and consequently its clearing as deforestation (Fearnside, 2017). It is also important to distinguish between *net* and *gross* deforestation. Whilst *net* deforestation allows for regrowth, and thus subtracts the areas of secondary forest, *gross* deforestation refers to the conversion of forest to non-forest (Brown & Zarin, 2013). Geographically, the larges share of forest loss has occurred in the tropics (FAO, 2016). Locally, tropical deforestation represents one of the greatest threats to the world's most diverse ecosystems, whilst it globally stands responsible for almost one-fifth of overall greenhouse gas emissions (Burgess, Hansen, Olken, Potapov, & Sieber, 2012). In sum, it represents one of the greatest environmental issues of our time.

3.1.2 Forest Cover, Deforestation and Agriculture in Brazil

Due to the fact that almost 70% of the worlds largest rainforest, the Amazon, falls within Brazilian boarders, the country sustains 40% of the world's remaining tropical forest (Kirby et al., 2006). Consequently, Brazil is also the house of a complex and rich ecosystem, with a wide range of plants, animals, and insects (L. E. Andersen, 1996). However, Brazil has for several decades been ranging as the country with the highest rates of deforestation in the world (Global Forest Watch, 2018).

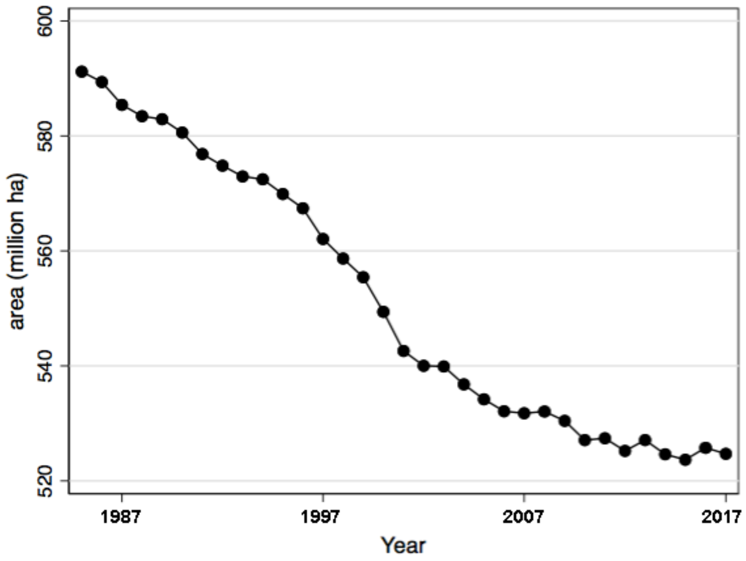
The "modern" era of deforestation began in the 1970s, with the opening of the Transamazon Highway (Fearnside, 2005). Up until this point, the Brazil's Amazon forest had remained largely intact. Form the mid 1970s, and throughout the 1980s, approximately 2.04 million hectares of forest was lost annually. The raging rates continued into the 1990s and the 2000s, however somewhat lower than the past two decades (Fearnside, 2005). In total, Brazilian forest loss between 1980 and 1995, was equivalent to one-fifth of total tropical forest loss during that time (Cattaneo, 2002). From 1996 to 2005, the average clearing per year amounted to 1.95 million hectares (Nepstad et al., 2009). Panel A of Figure 1 shows how total Brazilian forest cover has decreased from 1987 to 2017. In the period of interest, from 1996 to 2006, total forest cover decreased rapidly, before flatting out between years 2006-2017.

On of the greatest drivers of deforestation is increased demand for cropland (Ehui & Hertel, 1989). During the second half of the twentieth century, the amount of land devoted to agriculture in Brazil expanded considerably, and from 1960 to 1985 farmland grew from covering 29% to 44% of the country's territory (Assuncao et al., 2016). The Brazilian economy is heavily dependent on the agricultural sector (Martinelli, Naylor, Vitousek, & Moutinho, 2010), with soybeans, sugar, beef, coffee and corn as some of their main export products (OEC, 2016). Numbers from the National Confederation of Agriculture and Livestock shows that the agricultural sector accounted for 46.2% of all the country's exports in 2016 (BrazilGovNews, 2017). In sum the sector accounts for 26% of Brazil's GDP, and provides 32% of all Brazilian jobs. Panel B of Figure 1 shows how total agricultural land cover has developed in Brazil from 1987 to 2017. As displayed in the figure, agricultural land cover has experienced a steady increase, from covering an area of around 20 million hectares in 1987, compared to an area of approximately 53 million hectares in 2017[2].

According to FAO, approximately 284 million hectares of Brazilian land is devoted to agriculture (FAO, 2018a). However, the rise of the agricultural sector has its downsides, as there is a close link between the expansion in land use for agricultural production and deforestation (Assuncao et al., 2016). Thus, the Brazilian rainforest and ecosystems have paid a high price for the success of the country's agricultural sector, as agricultural expansion has been accompanied by massive deforestation (Martinelli et al., 2010).

[2]Please note that these data do not include pasture, compared to farmland referred to in the sentence above.

PANEL A. Development in Total Forest Cover 1985-2017



PANEL B. Development in Total Agricultural Land Cover 1985-2017

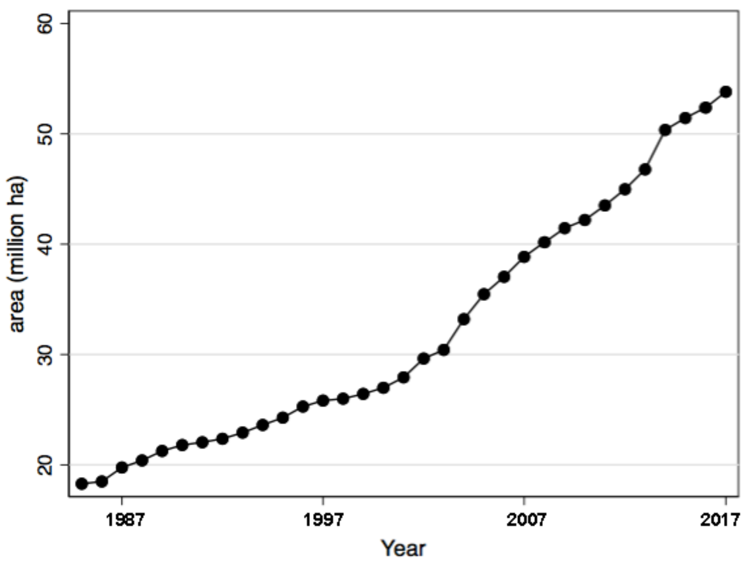


Figure 1: Forest Cover and Agricultural Land Cover in Brazil

Notes: Total area of forest cover and agricultural land cover in Brazil measured in hectares based on data from the MapBiomas Project map statistics database (2018a). Forest cover includes forest formations, savanna formations and mangrove. Agricultural land cover includes annual and perennial agriculture and semi-perennial agriculture.

3.2 Technical Change in Brazilian Agriculture

3.2.1 Genetically Engineered Soy Seeds

In 2017, Brazil accounted for 30% of the global production of soybeans, defining them as the second largest producer (USDA-FAS, 2017), and the number one exporter of soybeans worldwide (USDA, 2018). The economical importance of agriculture described in Subsection 3.1.2, emphasizes the need of land for agricultural activities, and soybeans are competing for farmland with other crops and livestock (Schnepf, Bolling, Dohlman, et al., 2001). This is also displayed in Panel A in Figure 2, which shows that area planted with soy experienced a steep growth from 2000 until 2011.

In relation to the growing world population and efforts made to ensure food security, the use of biotechnology, such as GE seeds, can substantially improve yields (Qaim & Kouser, 2013). According to agriculture engineers, plant diseases, pests and invasive species are the main causes of the financial losses in agriculture (Paini et al., 2016). This highlights the main advantage of GE soy seeds relative to traditional ones. Whereas traditional soy seeds require soil preparation in the form of tillage, GE soy seeds are herbicide-resistance, and therefore there is no need of tillage (Fernandez-Cornejo & McBride, 2002). Tillage can be explained as a manual clearing and preparation of soil, and involves removing weeds that compete with the soy seeds for water and nutrition, or threatens to crowd it out. GE soy seeds, on the other hand, can be applied directly on last seasons soil, since applying herbicide will eliminate unwanted weeds without harming the soy crop. Hence, there are significant financial benefits by adopting GE soy seeds (Duffy & Smith, 2007). As shown in Panel D of Figure 2 soy production per worker has increased substantially during the last decades (Bustos, Caprettini, & Ponticelli, 2016).

GE soy seeds was developed in the United States in 1996, by the agriculture biotechnology firm Monsanto (Fernandez-Cornejo, 2009). As a result of pressure from the agribusiness in Brazil, the technology was legalized by the Brazilian government in 2003. However, according to United States Department of Agriculture (USDA), the GE seeds had already been illegally grown in the south of the country since 2001, due to the seeds being smuggled in from Argentina (USDA, 2001). In 2006, GE plants constituted 46.6% of the area cultivated with soy in Brazil (IBGE, 2006). According to numbers from the Foreign Agriculture Service of the USDA, the adoption rate of GE soybean seeds was at 93% in 2017 (João & Nicolas, 2017).

3.2.2 Second Harvesting Season of Maize

Over the last decades Brazilian maize cultivation has experienced significant changes (CONAB, 2012), and the country is currently the third largest maize producer in the world (Pires et al., 2016). One of the main drivers of this growth in production of maize has been extensive adoption of double cropping systems. In the early 1980s a second season of maize production was introduces in Brazil by some farmers South-East in the country (CONAB, 2012). This second season of maize, also called milho safrinha, is cultivated after the summer, between March and July. In comparison to the rapid adaption of GE soy seeds, as described in the previous subsection, the second season of maize did not experience the same speed of adoption. Rather, the technique was gradually adopted around the country, with high presence in the state of Mato Grosso. However, the use increased significantly from 2008 (Allen & Valdes, 2016). Panel E of Figure 2 illustrates that total area planted with maize experienced a slight increase from 1980 until 2010. However, meanwhile the area planted with first season maize decreased from 1995 and on, the use of a second season maize has increased steadily.

In order to grow a second season of maize the farmers need modern cultivation techniques (EMBRAPA, 2010). Thus, milho safrinha can be argued to be a technical change. The clearing of soil require preparation which differ from the regular cultivation of first season maize, both in terms of fertilizers and herbicides (CONAB, 2012). As for GE soy, soil preparation for second season maize is a no-tillage system (Givens et al., 2009). Double cropping leads to more intense use of soil, which removes the nitrogen. Thus, this has to be replaced by fertilizers. Further, in order to prepare the soil for a second season on time, the technique requires herbicides to clear away remaining parts after the first season. Consequently, in comparison with a fist season maize, nematodes, diseases and pests are better controlled for with second season maize. In addition, the timing is essential and planting needs to happen one month faster than the first crop, hence higher mechanization are required (EMBRAPA, 2010). Due to these factors, second season maize is labor intensive, contrary to GE soybean production (Bustos et al., 2016).

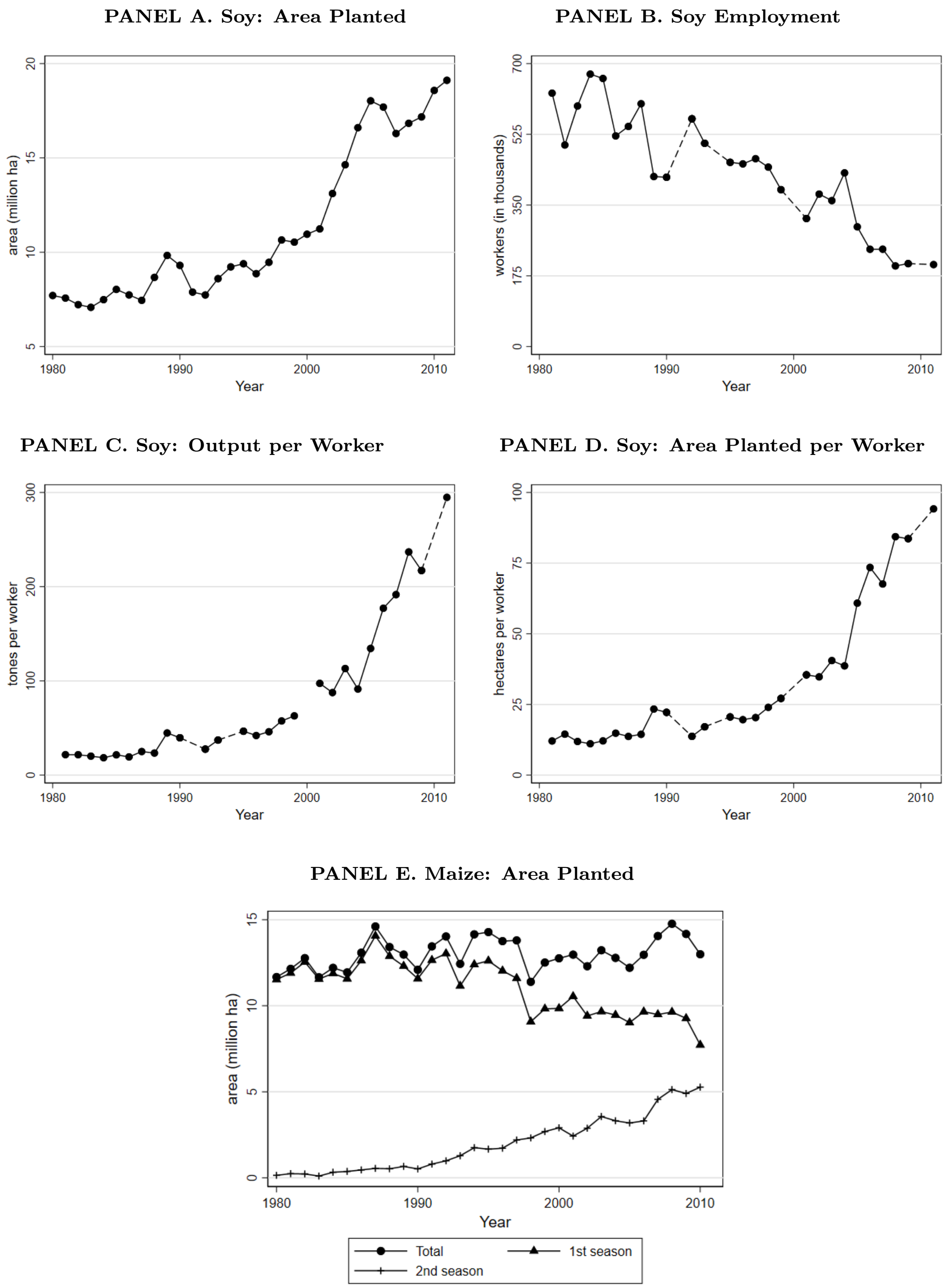


Figure 2: Soy and Maize in Brazil

Notes: The panels are replications of Bustos et al. (2016). Data sources are CONAB (2018) and the Pesquisa Nacional de Amostra de Domicilios (PNAD) survey conducted by IBGE. The data used on soy output, area planted with soy and area planted with maize in first and second season is from CONAB, while data on number of workers employed in soy production is from PNAD. The data is at state level. The states of Rondonia, Acre, Amazonas, Roraima, Pará, Amapá, Tocantins, Mato Grosso do Sul, Goias, and Distrito Federal are excluded in panel A–D due to incomplete coverage by PNAD in the early years of the sample.

4 Model

The goal of this thesis is to study how factor-biased technical change in agriculture affect forest and agricultural land use. Thus, in this section we present a simple economic model to illustrate the effect of factor-biased technical change on land and labor demand. The theories presented in this section are parts of a significant amount of economical literature on the subject. However, we choose to apply what we consider to be the most relevant and suitable in relation to our topic. The theories form the basis of our empirical predictions and are inspired by the model and findings presented by Bustos et al. (2016). However, whilst Bustos et al. (Bustos et al., 2016) focus their model on the effect of technical change on structural transformation, and thus the share of labor used in production, our thesis will focus on share of land used in production.

4.1 Setup

We consider a farmer that uses two production factors, land (T_a) and labor (L_a), in the production of either soy or maize. Production of both agricultural goods requires labor and land, and the production function takes the following form:

$$Q_a = f(L_a, T_a) \tag{1}$$

The marginal product of land, the change in output resulting from supplying one more unit of T_a, is given by $MPT_a = \frac{\partial f}{T_a}$. Similarly, the marginal product of labor is given by $MPL_a = \frac{\partial f}{L_a}$. The marginal technical rate of substitution (MRTS), the amount that one input must decrease, in order to maintain the same level of output, when adding one extra unit of the other input (Goolsbee, Levitt, & Syverson, 2013), is given by the following equation:

$$MRTS = \frac{MPL_a}{MPT_a} \tag{2}$$

Equation (1) and (2) briefly describe the relationship between land and labor in production, as well as how the quantity of these inputs relates to the quantity of output. Further, by introducing cost of production, we aim to explain how the equilibrium quantity of land is determined.

4.2 Equilibrium

In equilibrium the amount of land and labor used in production depends on the prices of these inputs, i.e. the wage rate (p_L) and the cost of land (p_T). In what follows, we assume these prices to be exogenous and given outside of the model. Thus, in production, the farmer faces a total cost of production C_a:

$$C_a = p_L L_a + p_T T_a \tag{3}$$

In order to maximize revenue, we assume that the farmer will minimize cost of production. Cost minimization implies that the value of the marginal rate of technical substitution must equal the ratio of the wage rate to the rental cost of land (Goolsbee et al., 2013):

$$\frac{MPT_a}{MPL_a} = \frac{p_T}{p_L} \tag{4}$$

$$\frac{MPT_a}{p_T} = \frac{MPL_a}{p_L} \tag{5}$$

Equation 5 illustrates that, in equilibrium, using one extra dollar on increasing either the amount of land or labor in production, should yield the same increase in production. As a result, in equilibrium, any given output (Q_a) can be produced at minimum cost, using an optimal combination of labor input (L_a) and land input (T_a). The optimal combination of the two inputs, corresponding to any level of output, is given by the expansion path (Ringstad, 2002), as illustrated in Figure (3):

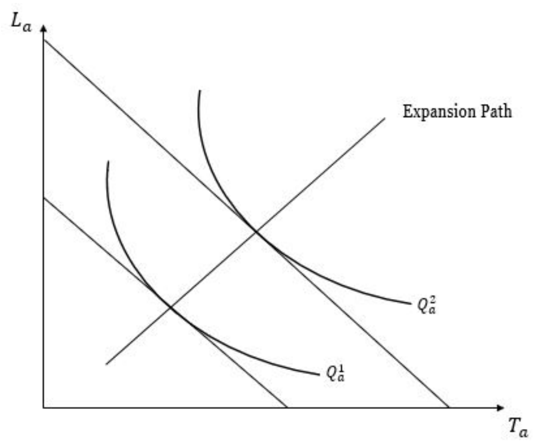


Figure 3: Cost Minimization and Optimal Combination of Land and Labor
Source: Own

4.3 Technological Change and Land Use

In this subsection we exploit the equilibrium presented in the previous subsection to investigate how technological change affects the equilibrium allocation of land. More specifically, we assess the response of the amount of land used in production to three types of technical change; Hicks-Neutral, Labor-Augmenting and Land-Augmenting.

4.3.1 Hicks-Neutral Technical Change

Hicks-neutral technical change implies that every combination of the two inputs, land and labor, gives a higher level of production than before. Consequently, the original level of production can be produced at lower costs, as illustrated in Figure 4. However, the optimal composition of land and labor in production, and thus also the expansion path, remains unchanged (Ringstad, 2002).

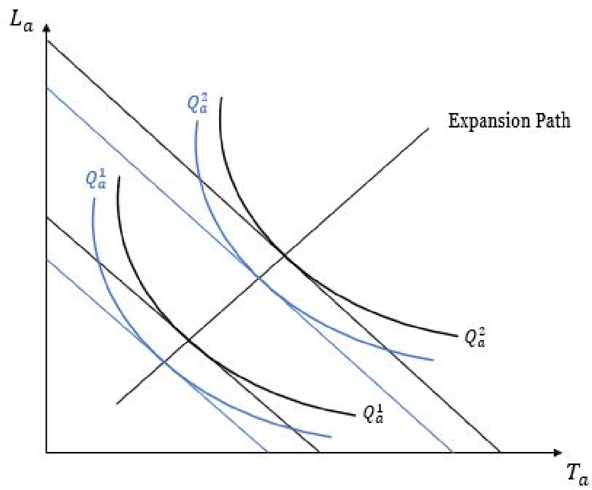


Figure 4: Hicks-Neutral Technical Change
Source: Own

4.3.2 Factor Biased Technical Change

In the case of factor-biased technical change, economic theory implies that, given unchanged factor prices, the optimal relative composition of land and labor will change. That is to say, in equilibrium, the farmer will produce using more of one input and less of the other. Hence, in the case of non-neutral technical change, the location of the expansion path will change (Ringstad, 2002).

Land-Augmenting Technical Change:

Land-augmenting technical change makes land relatively more productive, and implies that every level of output can be produced using less land and more labor, both in relative and absolute terms. Consequently, this type of technological change shifts the expansion path in the north-west direction (Ringstad, 2002), as illustrated in Figure 5. As a consequence, land-augmenting technical change causes the level of land used in production, relative to labor, to decrease.

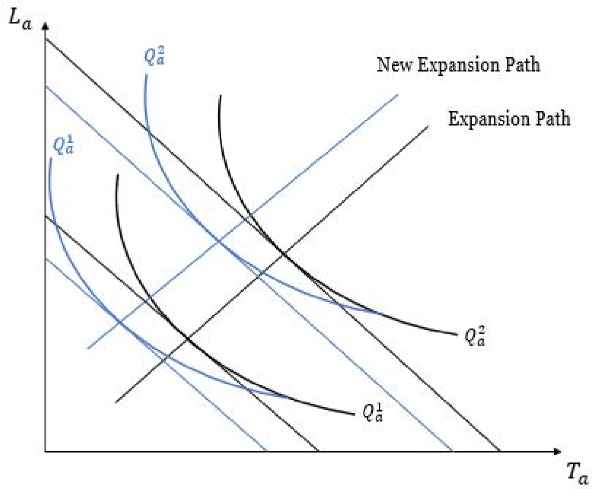


Figure 5: Land-Augmenting Technical Change
Source: Own

Labor-Augmenting Technical change:

Labor-augmenting technical change makes labor relatively more productive, and implies that every level of output can be produced using less labor and more land, both in relative and absolute terms. Consequently, this type of technological change shifts the expansion path in the south-east direction (Ringstad, 2002), as illustrated in Figure 6. As a consequence, labor-augmenting technical change causes the level of land used in production, relative to labor, to increase.

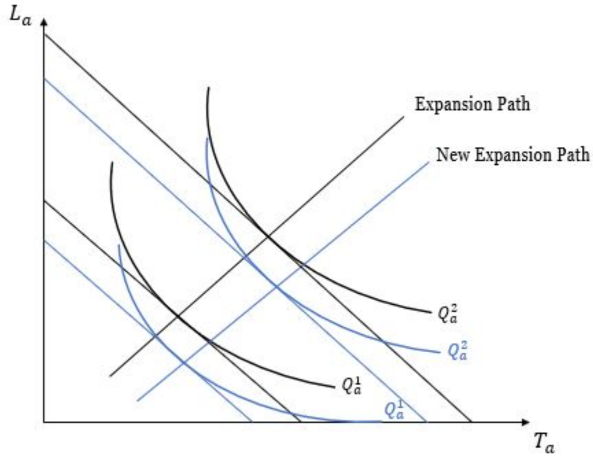


Figure 6: Labor-Augmenting Technical Change
Source: Own

4.3.3 The Effect of Factor-Biased Technical Change on Factor Demand

According to Ringstad (2002), factor-biased technical change generates three different effects that all influence factor demand. First, a given quantum can be produced using less of both inputs, pulling in the direction of decreased demand for both inputs. Second, technical change decreases both marginal and average cost of production, implying that increased production will be profitable. Thus, this second effect is pulling towards increased demand for both inputs. Third, factor-biased technical change in land (labor) generates a twist away from the demand for land (labor), towards the demand for labor (land). Accordingly, two effects are pulling towards decreased demand for the input exposed to technical change, whilst one effect is pulling towards increased demand. Regarding the input not affected by technical change, two effects are pulling towards increased demand for this input, whilst one effect is pulling towards decreased demand. Hence, the net effect for both inputs is unclear. However, the predictions presented in this section is based on the simple assumption that the effect twisting demand away from the input exposed to technical change has a dominant effect.

Through an empirical analysis of the effect of land- and labor augmenting technical change, the aim of this thesis is to investigate the effect of factor-biased technical change on demand for land in agriculture. In addition, we aim to examine how this change in demand affects forest; either through an expansion in agriculture at the expense of forest, or through reduced amount of land in agriculture reducing the pressure on forest.

4.4 Empirical Predictions

As Bustos et al. (2016), we test the theories presented in our model by studying the simultaneous expansion of the two agriculture technologies described in Section 3. The introduction of GE soy seeds reduced the farmers need to plow the land, as a result of the seeds being herbicide-resistant. Thus, compared to using traditional seeds, less labor per unit land is required to yield the same output. As a consequence, the introduction of GE soy can be described as labor augmenting change. In the case of maize, introduction of advanced cultivation techniques made farmers able to cultivate maize in a second season. This technology effectively increased the land endowment, and a second harvesting season of maize can therefore be described as land-augmenting technical change.

In our analysis we use an instrumental variable approach to quantify the effects of these two types of technical change on observable variables of forest and agricultural land in Brazil. The analysis aims to test the following predictions:

PREDICTION 1: *Land-augmenting technical change in agriculture;*
Decreases the need for land in agricultural production and reduces the pressure on forests

PREDICTION 2: *Labor-augmenting technical change in agriculture;*
Increases the need for land in agricultural production and increases the pressure on forests

5 Data

In this section we describe the data used in order to investigate the effect of technical change in agriculture on forest and agricultural land use in Brazil. Our data are drawn from three main sources. Data on land cover and land transition in Brazil are collected from MapBiomas Project (2018a). The data constructed by Bustos et al. (2016), most importantly the variables measuring technological change in agriculture, are drawn from the FAO-GAEZ database (2018b). In addition, we exploit variables drawn from the Brazilian Agriculture Census (1996, 2006) and PAM (2016), both from Instituto Brasiliero de Geografia e Estatística (IBGE).[3]. In the following subsections, we describe our data and their sources in detail.

5.1 Data on Forest and Agricultural Land

Data on land cover and land transition are collected from the MapBiomas Project map statistics database (MapBiomas, 2018a), and ranges from 1985 to 2017. MapBiomas is a multi-institutional collaboration established in 2015 by the initiative of several universities, NGOs and technology companies. The aim of the project is to develop a reliable and low-cost method to produce annual temporal series of land cover and transition maps and data of Brazil. The series are generated using pixel-per-pixel classification applied to satellite images (MapBiomas, 2018b). The process is conducted using extensive machine learning algorithms, and the source of the satellite images is the Landsat Data Archive (LDA), available in the Google Earth Engine platform. The project consists of three collections, whereby this thesis take advantage of the last one, Collection 3.0, published September 22^{nd} 2018.

Our dataset includes data on land cover and land transition for the whole of Brazil, for all six biomes: Amazonia, Caatinga, Cerrado, Mata Atlatica, Pampa and Pantanal. All data are reported by state and municipality. The data consists of classes at three levels, with five main classes included at the first level; (1) Forest, (2) Non-forest natural formations, (3) Farming, (4) Non-vegetated areas and (5) Water bodies. In our dataset, we only utilize data from the classes Forest and Farming. For a complete list of the sub-classes included in each class, please refer to Appendix A.1. To the best of our knowledge, no study related to forest and agricultural land use has applied land cover data on the whole of Brazil at municipality level.

We obtain our dependent variables from the MapBiomas database. More specifically, the variables *Forest Cover*[4], being the amount of land covered with forest, *Agricultural land*

[3]For a complete list of variables and how they are calculated, please refer to Appendix A.10.
[4]Including forest formations, savanna formations and mangrove

cover[5], being the amount of land devoted to agriculture, *Transition of land from forest to agriculture*, being the amount of land converted from forest to agricultural land, and *Transition of land from agriculture to forest*, being the amount of land converted from agricultural land to forest. We use the software R to reorganize the data sets, including structuring all sub-classifications of forest and farming as separated variables. All variables are measured in square kilometres.

The reasoning behind including both *Forest Cover* and *Agricultural land cover*, is to make our analysis more informative. This enables us to investigate how technological change in agriculture affects both the land used for agricultural activities and forest. The main motivation behind including the transition data is to make the analysis more robust. These variables demonstrate explicit information about areas covered with forest (agriculture) in 1995, which were converted into areas covered with agriculture (forest) land by 2005. Hence, by using the transition variables we manage to rule out all other types of land use expanding into forest or agricultural land cover, e.g. pasture, infrastructure or mining.

We argue for using data on land cover based on our predictions that the two different types of technical change will have opposite effects in terms of demand for agricultural land. Whereas land-augmenting technical change, in the form of second season maize, is expected to decrease demand for land in maize production, labor-augmenting technical change, in the form of GE soy seeds, is expected to increase demand for land in soy production. Hence, the double cropping technology may lead to natural regrowth due to decreased demand for land in maize production. We allow for this when using the variable *Forest Cover*, because this variable includes regrowth in forest and accordingly constitutes *net* deforestation. In the case of the variable *Transition of land from forest to agriculture*, regrowth is not included, and this variable is therefore a gross measure of deforestation. In comparison, the variable *Transition of land from agriculture to forest* is a measure of regrowth in forest.

For the variables *Forest cover* and *Agricultural land cover*, we use data from 1996 and 2006. With regard to the variables *Transition of land from forest to agriculture* and *Transition of land from agriculture to forest*, we obtain transition of land use over a 10 year period. Because of inadequate yearly data for these variables, we collect data for two five year periods, 1995-2000 and 2000-2005 respectively. Further, we calculate the sum of these two periods, in order to obtain the total amount of land converted from forest(agriculture) to agriculture(forest) during the period of interest.

[5]Including annual and perennial agriculture and semi-perennial agriculture

5.2 Agricultural Data

5.2.1 The FAO-GAEZ Database

Variables measuring the effect of technological change in soy and maize are from the dataset developed by Bustos et al. (2016). The authors have constructed the variables by exploiting estimates of potential soy and maize yields under different inputs across geographical areas of Brazil. The estimates of potential yields are obtained from the FAO-GAEZ v3.0 database (2018b), and have been constructed using a soil suitability index.

The soil suitability index, shown in Figure 7, is developed by FAO, in cooperation with the International Institute for Applied Systems Analysis (IIASA), and has been produced using the Agro-Ecological Zones (AEZ) model (FAO, 2018b). The aim of the AEZ model is to assess agricultural resources and potential. The index is constructed by exploiting knowledge on crop requirements, soil conditions and soil management (FAO & IIASA, 2018c). More specifically, the measures of soil suitability are used to quantify to what extent the soil conditions in a given area match crop requirements, given defined input and management circumstances. The model has been applied considering the average climate of the period 1961-1990 (Bustos, Caprettini, & Ponticelli, 2018).

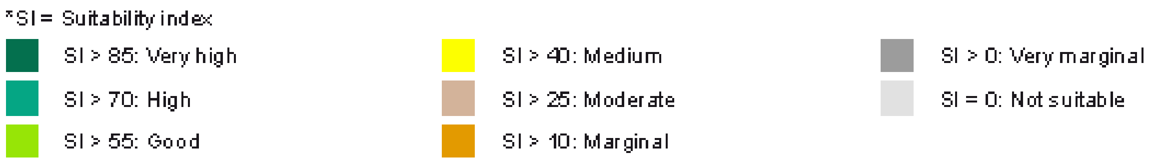


Figure 7: Crop Suitability Index

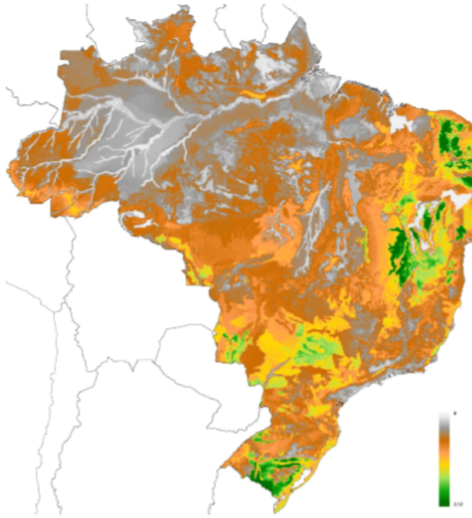
Source: Obtained from FAO & IIASA, 2018a

In addition, the AEZ model can be used to provide information about potential yields under different technologies, or so-called input combinations. The database separates between low, intermediate and high level inputs, where the different input levels reflect the level of cultivars, labor intensity, nutrient and machinery used in production. For a detailed description of the different input levels, please refer to Appendix A.10. The variables on potential soy and maize yields across Brazil have been calculated by exploiting measures of potential yields under different input levels (Bustos et al., 2018). More specifically, the variables capturing the effects of technical change in production of soy and maize has been calculated by subtracting the variable indicating crop yields under the low input level from the variable indicating crop yields under the high input level for each municipality. Yields under the high input level are meant to capture the use of optimal mechanization and application of fertilizers and herbicides, such as genetically engineered seeds or advanced cultivation techniques (FAO & IIASA, 2018a). In contrast, the low level categorization is meant to cover yields obtained planting traditional seeds, with no use of chemicals or mechanization. Thus, we refer to the low input level as using low technology, whilst we refer to the high input level as using high technology. All variables are given in tons per hectare.

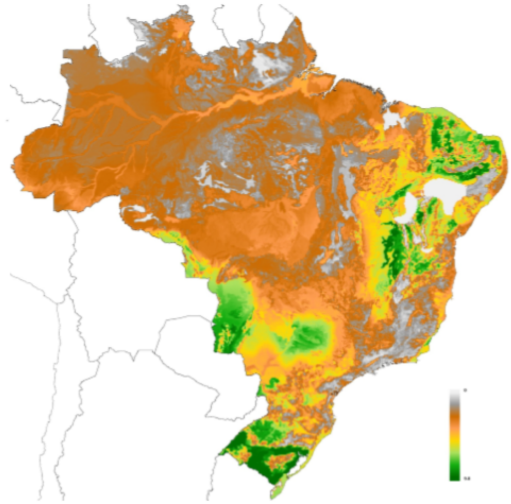
The effect of the different levels of technology on potential soy(maize) yields is illustrated in Figure 8. Panel A and B illustrate the effect on potential maize yields when moving from low to high technology, whilst Panel C and D illustrate the same regarding potential soy yields. Panel E illustrates the change in potential soy yields when subtracting the variable indicating soy yield under the low input level from the variable indicating yields under the high input level.

Because potential yields are a function of weather and soil characteristics, and not of actual yields in Brazil, we argue that they can be used as a source of exogenous variation in agricultural productivity across geographical areas. This will be explained more in depth in Subsection 6.3.

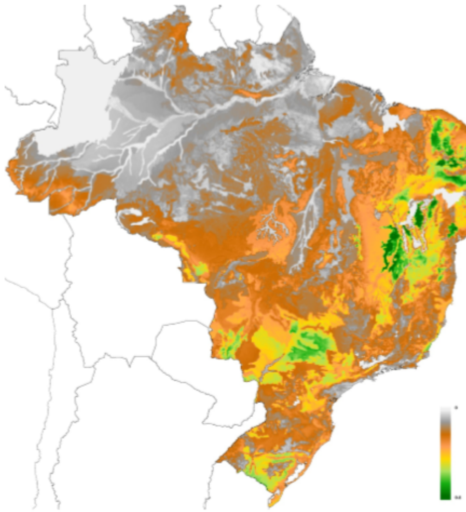
PANEL A. Potential maize yield under low technology



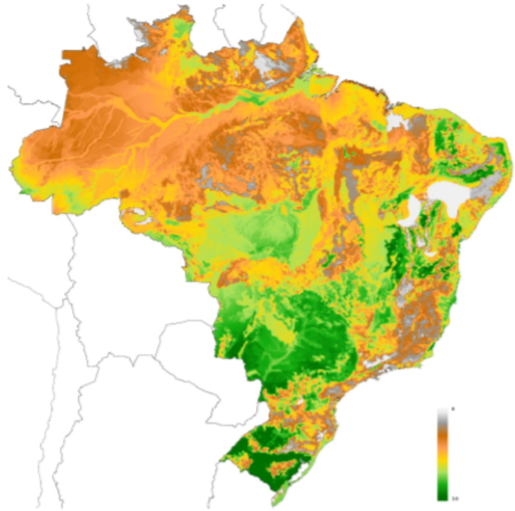
PANEL B. Potential maize yield under high technology



PANEL C. Potential soy yield under low technology



PANEL D. Potential soy yield under high technology



PANEL E. Change in potential soy yield: high minus low technology

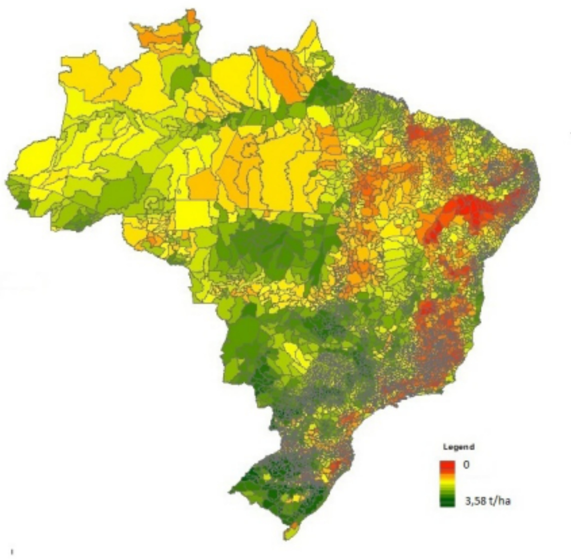


Figure 8: Measure of Technological Change in Soy and Maize

Notes: Created by Bustos et al. (2016) Source: Bustos, Caprettini, & Ponticelli, 2018, Online Appendix. Based on data from FAO-GAEZ (FAO & IIASA, 2018b).

5.2.2 The Agricultural Census

The agricultural census is released every tenth year by IBGE (1996, 2006), the Brazilian National Statistical Institute. The last two rounds were carried out in 1996 and 2006, and were collected through interviews with the managers of each agriculture establishment (Bustos et al., 2016). The main variable of interest constructed by Bustos et al. (2016) from the census is the variable *GE soy area share*, defined as area (in hectare) reaped with GE soy divided by total land in farms.

In addition to the variables in the dataset developed by Bustos et al. (2016), we have obtained data directly for IBGE and the agricultural census, in order to construct two additional variables; *Total land in farms* in 2006 and *Area cultivated with GE soy* in 2006. The motivation for obtaining total land in farms is to enable us to construct a variable equal to the total area reaped with second season maize divided by total land in farms, *second season maize area share*. Consequently, this variable is meant to complement the variable *GE soy area share* in the dataset developed by Bustos et al. (2016) The reasoning behind including a variable on area cultivated with GE soy in our dataset, is that this enables us to investigate the effect of a general expansion of GE soy and second season maize independent of other agricultural crops. All data are collected at municipality-level.

5.2.3 SIDRA: Produção Agrícola Municipal

Data on area cultivated with first and second season maize have been obtained from the Produção Agrícola Municipal (PAM) database (IBGE, 2016). PAM is a database providing the results of a survey conducted every year by IBGE. The aim of the survey is to provide statistical information on quantity produced, area planted and harvested and average yields of certain crops in Brazil (IBGE, 2016). All data are collected at municipality-level.

5.3 Geographical Units

To combine our data with the dataset constructed by Bustos et al.(2016), we aggregate all data at AMC level for all municipalities using the same method as Buto et al. (2016), i.e. the correspondence proposed by IPEA and IBGE. Since boarders of Brazilian municipalities often change, IBGE has defined Área Mínima Comparável (AMC), smallest comparable areas, in order to make them comparable over time (IBGE, 2011). Consequently, we use AMC as our unit of observation. All variables from MapBiomas, the Agricultural Census and the FAO-GAEZ database have been aggregated from municipality level to the level of AMC, using the correspondence proposed by IPEA and IBGE. Accordingly, we transform our data from covering 5,570 number of municipalities to cover 4,255 number of AMC units. In terms of land size, the average size of a municipality is 1,500 square kilometers, whilst the average AMC has an area of 2,000 square kilometers (Bustos et al., 2016). With regard to population, the average municipality and AMC have 30,883 and 39,858 inhabitants, respectively. In the remainder of the paper we will refer to AMCs as municipalities.

6 Empirical Strategy

The goal of our empirical analysis is to identify the causal effects of the adoption of new agricultural technologies on various land use outcomes in Brazil. More specifically, our four outcomes of interest are *Forest cover*, *Agricultural land cover*, *Transition of land from forest to agriculture* and *Transition of land from agriculture to forest.* Our estimation strategy is an IV approach, inspired by the empirical strategy used by Bustos et al. (2016). However, whilst these authors focus their analysis on conducting a reduced form estimation, we have expanded this approach by including a 2SLS estimation. More specifically, through the use of two instrumental variables, we investigate how the adoption of two new agricultural technologies, GE soy and a second harvesting season for maize, affect agricultural land use and forests.

We attempt to establish a causal relationship between agricultural productivity and our outcomes of interest by exploiting two sources of exogenous variation in the profitability of technology adoption. First, we utilize the exogenous expansion of these technologies as a source of variation across time. Second, we exploit the different impact these technologies had on potential crop yields across geographical areas in Brazil. Consequently, we assume that the adoption will produce an exogenous shock that affects our outcome variables.

6.1 The Instrumental Variables Approach

The method of IV is a useful tool in order to overcome several problems of causal inference. Firstly, IV estimation can be used as a way of dealing with problems of endogeneity. A potential problem when estimating a causal relationship between two variables, can be that the explanatory variable is correlated with unobserved factors also affecting the outcome of interest (Bound, Jaeger, & Baker, 1995). This implies that the explanatory variable is endogenous and correlated with the error term, and would cause the estimated regression results using ordinary least squares (OLS) to be biased and inconsistent. A second use of IV is to overcome problems of omitted variable bias (OVB), in other words the problem of missing unknown variables affecting the outcome of interest (J. Angrist & Krueger, 2001). Thirdly, an IV strategy reduces the risk measurement error problems in the explanatory variables.

The method of IV hinges upon having access to a proper instrument. An instrument is a variable that is correlated with the explanatory variable of interest, but uncorrelated with any other variables correlated with the dependent variable (J. D. Angrist & Pischke, 2015). The first requirement implies that the instrument is relevant to explain changes the in explanatory variable. The latter requirement can be split in two parts (J. D. Angrist & Pischke, 2009). The first, called *the independence assumption*, is the assumption that the instrument is as good as randomly distributed across the observed variables of interest. The second, called the *exclusion restriction*, is the assumption that the instrument only affects the outcomes of interest through the explanatory variable, i.e. through the first-stage channel. In sum, these requirements are called the three assumptions of IV estimation. Whilst the first assumption of IV can be tested through the first-stage, there is no proper way to test the latter two.

The choice of a proper instrument is essential to any IV estimation. Additionally, one must have access to at least as many instrumental variables as there is endogenous variables. If the number of instrumental variables exactly equals the number of endogenous variables, the model parameters are characterized as *exactly identified*. Contrarily, if the number of instrumental variables exceeds the number of endogenous variables, the model parameters are characterized as *overidentified* (Hill, Griffiths, Lim, & Lim, 2008).

Formally, IV estimation is conducted in two stages, where the first-stage is regressing the explanatory variable on the instrument. The aim of this stage is to test whether there is a statistically significant correlation between the instrument and the explanatory variable of interest (J. D. Angrist & Pischke, 2015), and thus to assess whether the instrument can be considered strong or weak (Hill et al., 2008). The first-stage is also used to obtain the two-stage least squares (2SLS) estimator, a new fitted value of the explanatory variable. Further, the second stage is regressing the dependent variable on this estimator (J. D. Angrist & Pischke, 2009).

6.2 Instrumenting the Expansion of GE soy and Second Season Maize

The motivation behind using IV estimation as our empirical approach, is the problem of OVB. Additionally, a potential problem can be inherent endogeneity between adoption of new agricultural technologies and land use. As mentioned in Section 1, a new technology is not necessarily adopted randomly across space or time, but rather in places where complementary factors are cheap and available. For instance, it is possible that cultivation of GE soy and second season maize expanded as a result of increased development in infrastructure in order to facilitate agricultural activities. Improved infrastructure could also lead to an increase in other activities, such as livestock farming, which again could have an effect on agricultural land use and forests. If this would be the case, there is an endogeneity problem in the model. Consequently, in order to properly estimate the effect of technological change on agricultural land use and forest, without the estimates being correlated with any unobserved variables, an instrument is necessary.

Similarly to Bustos et al. (2016), we exploit the FAO-GAEZ potential yield for soy and maize as an exogenous measure of technological change. As mentioned in Subsection 5.2.1, the low technologies are described as those using traditional seeds, with no use of chemicals and mechanization. The high technology is described as using improved seeds and modern mechanized cultivation techniques. Consequently, we expect the difference in yields between using the high and low technology to capture the effect of moving from traditional agriculture to technology that uses improved seeds, optimum weed control and a high use of machines (Bustos et al., 2018). Thus, the increase in soy yields is expected to be a good predictor of the profitability of adopting herbicide-resistant GE soy seeds. In the case of a second harvesting season of maize, this method requires modern techniques involving intensive use of fertilizers, herbicides and machinery (CONAB, 2012, EMBRAPA, 2010). Therefore, we expect the differences in FAO-GAEZ potential maize yields between using high and low technology to capture the profitability of introducing this new cultivation technique. Because potential yields are a function of weather and soil characteristics, and not of actual yields in Brazil (Bustos et al., 2016), we argue that these can be considered as exogenous across municipalities. Thus, we use this measure of potential yields of soy and maize as instruments for the expansion of GE soy and second season maize, i.e. technical change in agriculture.

In an effort to isolate exogenous variation in our explanatory variables, we estimate the following first-stage equation:

$$x_{jt} = \delta_j + \delta_t + \beta^{soy} A^{soy}_{jt} + \beta^{maize} A^{maize}_{jt} + \varepsilon_{jt} \tag{6}$$

where the dependent variable x_{jt} is the area of land devoted to either GE soy or second season maize for municipality j at time t. δ_j are municipality fixed effects, capturing any unobserved time-invariant variables at the municipality level. δ_t are time fixed effects, capturing the effect of a specific year affecting all Brazilian municipalities. Hence, any time-specific events are controlled for by these year fixed effects. In addition, any unobserved variables, fixed at the municipality level, is absorbed by the municipality fixed effects. A^{soy}_{jt} is the instrument for GE soy expansion. This variable takes the value corresponding to yields using low inputs before 2003, and the value corresponding to yields using high inputs after. Thus, A^{soy}_{jt} can be viewed as the empirical counterpart of the labor-augmenting technical change presented in our model. Similarly, A^{maize}_j is the instrument for the expansion of a second harvesting season in maize, and captures the profitability of adopting the new technology in maize. Thus, A^{maize}_j represents the empirical counterpart of the land-augmenting technical change. ε_{jt} is the time-varying error and contains both fixed errors v_j, caused by unobserved time-invariant variables, and a random error component, u_{jt}.

The aim of the first-stage regression is to investigate whether change in potential yields can serve as a good instrument for the profitability of adoption of the new agricultural technologies. More specifically, we explore whether potential yields in soy and maize can predict where second season maize and GE soy expanded. If so, we expect the increase in potential yield of a given crop to predict the actual expansion in area of agricultural land cultivated with that crop between 1996 and 2006. We expect the areas with a high increase in potential soy yields to be those adopting genetically engineered soy on a larger scale. Similarly, we expect the areas with a high increase in potential maize yields to be those adopting a second harvesting season of maize on a larger scale. In order to evaluate the strength of the instrument, we use the criterion of an F-statistic above 10 proposed by Staiger and Stock (1994). The rule of thumb is that an instrument with an F-statistic below 10 should be considered weak.

Our period of analysis spans from 1996 to 2006, the years between the last two agricultural censuses. Because fixed effects and first difference estimates are identical when considering only two periods (Wooldridge, 2016), we estimate equation (6) in first differences. Hence, in an attempt to eliminate the unobserved effect v_j and tackle the problem of omitted time-invariant unobservables, the first-stage equation becomes:

$$\Delta x_j = \Delta\delta + \beta^{soy}\Delta A_j^{soy} + \beta^{maize}\Delta A_j^{maize} + \Delta\varepsilon_j \tag{7}$$

where the variable of interest, Δx_j, is the change in the amount of land devoted to either GE soy or second season maize between the two census years. ΔA_j^{soy} is the potential yield of soy under the high technology, minus the potential yield of soy using the low technology. Similarly, ΔA_j^{maize} equals the potential yield of maize using high technology, minus the potential yields of maize under low technology.

The second stage relationship between the expansion of GE soy and second season maize, and the various land cover and land transition outcomes, is given by the following equation:

$$y_{jt} = \delta_j + \delta_t + \beta^{soy}x_{jt}^{soy} + \beta^{maize}x_{jt}^{maize} + \varepsilon_{jt} \tag{8}$$

where y_{jt} is the outcome variable of interest for municipality j at time t. x_{jt}^{soy} and x_{jt}^{maize} are instrumented using equation (7), and represents the amount of land devoted to GE soy and second season maize, respectively. δ_j are municipality fixed effects, and δ_t are time fixed effects. ε_{jt} is the time-varying error, and contains both fixed errors v_j, caused by unobserved time-invariant variables, and a random error component, u_{jt}.

Based on the same reasoning as for the first-stage equation, we estimate the 2SLS equation (8) in first differences[6]:

$$\Delta y_j = \Delta\delta + \beta^{soy}\Delta x_j^{soy} + \beta^{maize}\Delta x_j^{maize} + \Delta\varepsilon_j \tag{9}$$

where Δy_j is the change in the outcomes of interest between the two census years. Δx_j^{soy} and Δx_j^{maize} are the changes in the instrumented variables. Thus, the two coefficients of interest is β^{soy} and β^{maize}, indicating the effect of the expansion of the two new technologies on the different land outcomes.

6.3 Key Identifying Assumptions

As mentioned in Subsection 6.1, the first assumption of IV estimation, relevance of the instrument, can be tested through the first-stage regression. However, our identification strategy also hinges on the assumption that the timing of the introduction, and the adoption of the new technologies, is uncorrelated with the determinants of changes in land use. Additionally, the profitability of the new technologies has to be randomly distributed across Brazilian municipalities. Thus, in order to capture a causal effect, we exploit two sources of exogenous variation in the adoption of GE soy and second season maize. The first one being the timing of adoption of the different technologies, and the second their different impact on potential yields across geographical areas.

We argue that the timing of adoption of GE soy is likely to be exogenous with respect to developments in Brazilian land use. As mentioned in Subsection 3.2.1, GE soy seeds were developed in the United States and commercially released in the same country in 1996, and further legalized in Brazil in 2003. Consequently, it can be argued that the date of approval for commercialization in the United States, 1996, is exogenous with respect to development in the Brazilian land use. However, legalization in Brazil came largely as a response to pressure from Brazilian farmers, and reports of smuggling of GE soy seeds across the boarder from Argentina dates back to as early as 2001. Thus, to overcome these potential sources of endogeneity we compare outcomes before and after 1996.

[6]As mentioned in subsection 5.1, the variables *Transition of land from forest to agriculture* and *Transition of land from agriculture to forest* demonstrate explicit information about areas covered with forest (agriculture) in 1995, which were converted into areas covered with agriculture (forest) land by 2005. Consequently, because these variables measure transitions of land they are in themselves first-differences

Moreover, because of differences in soil and weather characteristics across Brazil, the new technology had a different impact on potential yields across the country (Bustos et al., 2016). As described in Section 5.2.1, the measures of potential yields in soy and maize are functions of weather and soil characteristics, and not of actual yields in Brazil. Hence, potential yields can be exploited as a source of exogenous variation in agricultural productivity across geographical areas, and in our analysis we exploit these exogenous differences as a source of cross-sectional variation in the intensity of treatment.

Contrary to GE soy, the agricultural techniques required to adopt a second harvesting season of maize were developed within Brazil. The timing of expansion can accordingly not be considered strictly exogenous to developments in land use. However, as Bustos et al. (2016), we argue that the expansion of the new technology across geographical areas is dependent on exogenous local soil and weather characteristics. Therefore, we claim that the variation in adoption can be viewed as exogenous to developments in agricultural land use and forests.

6.4 Choice of Functional Form

In our model, we include different functional forms of our dependent variables. More specifically, we include the variables both as total area, measured in square kilometres, and as the natural logarithm of the total area. There exists arguments for and against using either of these two different forms. When exploiting the variables as total area measured in level-form, we preserve the variation between the observations, and thus also the great differences in how the municipalities are affected by changes in the explanatory variables. However, this might also lead to significant results being caused by some extreme observations. As a consequence, the values of these regression might be overestimated. In an attempt to avoid this problem we calculate the natural logarithm of the variables. Figures in Appendix A.7 show that a log transformation of the variables reduce the skewness in the data considerably. This indicates that even if the data contains some extremes, the distribution of positive and negative observations are close to equal. However, the downside of a logarithmic transformation is that this may lead to loss of important variation in the data. This is in contrast to level-form, which maintains the great magnitudes of the dependent variables. However, if both the level-form model and the log-form model indicate the same effects of the explanatory variables, this would support the robustness of our results. Thus, we choose to include both functional forms in the analysis[7]. In our analysis, we focus on the model using a logarithmic transformation of

[7] In order to preserve observations with the value 0, we log transform the variables by using the *asinh* command in stata (asinh(x) = ln(x + sqrt(x*x + 1)))

our variables. However, when providing supplementary information, we discuss the results of the regressions with variables in original (level) form.

As for the dependent variables, we include the instrumented variables, agricultural land devoted to GE soy and second season maize, in both log and level form.[8]

6.5 Choice of Control Variables

When performing an IV estimation, the concern of OVB presents itself in a new form. An IV estimation is considered biased if there exists any omitted explanatory variables that is correlated with either the included explanatory variables or the instrumental variables. Consequently, one should have increased vigilance about omitted variables when conducting an IV estimation (Murray, 2006). Taking this into account, we include two control variables to our baseline equation. First, we control for municipalities being considered an agricultural frontier or not. Frontier municipalities are defined as those experiencing an increase in land use for agricultural activities between 1996 and 2006. We split the sample of municipalities in two groups: frontier and non-frontier[9]. The rationale behind including *frontier* as a control is that frontier municipalities are likely to experience higher growth in agriculture, including GE soy and maize cultivation, than non-frontier municipalities. Hence, we aim to control for different growth rate in agricultural activities across municipalities. Second, we include the variable *initial forest*, indicating the amount of existing forest in a given municipality in 1991, i.e. before the expansion of either GE soy or second season maize. As referred to in Section 2, Assunção et al (2016) find that the effect of technological change on forest loss depend on the prior amount of native vegetation. Thus, the reasoning for including this variable is because the amount of forest in a municipality is likely to be correlated with the magnitude of deforestation in the same municipality. In particular, we extend the main empirical specification by including these controls:

$$\Delta y_j = \Delta\delta + \beta^{soy}\Delta x_j^{soy} + \beta^{maize}\Delta x_j^{maize} + \gamma \boldsymbol{X}_j + \Delta\varepsilon_j \tag{10}$$

where the additional term, $\mathbf{X}_j$, is a vector including our control variables.

[8]In addition, similarly to Bustos et al., we also estimate our regressions using share of agricultural land devoted to the two different crops as instrumented variables. Please refer to Appendix A.3 for this analysis.

[9]For a description of frontier and non-frontier municipalities, please refer to Appendix A.2.

6.6 Reduced Form

Unlike most IV analysis, we begin our analysis by investigating the direct link between FAO-GAEZ potential yields and our outcome variables. That is, we estimate the reduced form relationship between change in potential yields and our outcomes of interest.

This approach is inspired by Bustos et al. (2016), who use potential yields as a proxy for the expansion in second season maize and GE soy in their empirical analysis. The advantage of the reduced-form approach is that it does not rely on excluding change in potential yields for soy and maize from a second stage equation (J. D. Angrist & Pischke, 2015). Hence, we avoid the possible problem of the *exclusion restriction* being violated. Similarly to Bustos et al. (2016), we expect that the increase in yields should serve as a good predictor of the profitability of adopting herbicide-resistant GE soy seed and second season maize. The main reasoning for this approach is that, in their data, Bustos et al. (2016) are not able to distinguish between different seasons of maize cultivation. In order to examine whether the change in potential yields can serve as a good proxy, Bustos et al. (2016) estimate the effect of technological change on expansion of total soy and maize cultivation, and not specifically GE soy and seconds season maize. Trough this exercise Bustos at al. (2016) conclude that changes in potential yields, when switching to the high technology can serve as good measures for crop-specific technical changes in soy and maize.

In this thesis we have obtained variables on second season maize from the PAM survey conducted by IBGE (2016), that enables us to make the distinction between second and first season maize cultivation. Nevertheless, based on the approach presented by Bustos et al, we begin our analysis by estimating a reduced form equation. More specifically, we regress the outcomes of interest directly on the instruments:

$$\Delta y_j = \Delta\delta + \beta^{soy}\Delta A_j^{soy} + \beta^{maize}\Delta A_j^{maize} + \gamma \boldsymbol{X}_j + \Delta\varepsilon_j \tag{11}$$

where the variables are defined as in the previous Subsections. The two coefficients β^{soy} and β^{maize} represents the effect of changes in potential yields of soy and maize on changes in our dependent variables defined in Section 5.1.

6.7 Reduced Form versus Two-Stage Least Squares

A drawback of the reduced form approach is that it does not allow for a clear identification of whether the observed effects are provoked by the adoption of the two different technologies. In Subsection 6.3, we argue that potential yields can be used as a source of exogenous variation in agricultural productivity because they are a function of weather and soil characteristics, not of actual yields in Brazil. Thus, despite being the foundation of our analysis, this assumption also constitutes a weakness. Even if we argue that change in potential yields should serve as good indicators for the expansion of GE soy and second season maize, we cannot be sure that our observed effects originates from the expansion of these two crops. Alternatively, the observed effects can be due to expansion of traditional soy and maize cultivation, or even other crops. Consequently, in order to examine and test the robustness of these results, we take the analysis of Bustos et al. (2016) one step further, conducting an 2SLS estimation using potential yields in maize and soy as instruments for second season maize and GE soy.

The motivation behind running a 2SLS regression is that an instrumental variable estimation should give stronger indications in favour of, or against, whether the reduced form estimations reflect the effects of adopting the two technologies. More specifically, we aim to investigate if potential yields in soy and maize can serve as proxies, for the profitability of adopting GE soy and second season maize. We believe that the 2SLS regressions can give a more distinct indication on whether or not the results, produced in the reduced form analysis, are caused by an expansion in GE soy and second season maize.

One implication of conducting a 2SLS regression is that it reimposes the potential problem of the exclusion restriction being violated. Another implication is that the data on area cultivated with second season maize only are available from 2003 on wards. This might explain why Bustos et al. (2016) choose not to use this variable in their analysis. However, due to scarce prevalence of second season maize in 1996, we assume this variable to be 0 in 1996.

7 Empirical Analysis

In the following section, we aim to estimate the effect of factor-biased technical change on agricultural land use and forest. The analysis consists of four main parts. First, we estimate the reduced form equation, performing a similar analysis as Bustos et al. (2016). Second, we estimate the first-stage regressions, evaluating potential yields as an instrument, or proxy, for technical change. Third, we run the instrumental variables regressions. Fourth, we present a heterogeneity analysis. Finally, we summarize our results.

7.1 Reduced Form Estimates

We begin our analysis by estimating Equation 11 presented in Section 6.1. The dependent variable, Δy_j, is the change in four different land use outcomes; *Agricultural land cover*, *Transition of land from forest to agriculture*, *Forest cover*, and *Transition of land from agriculture to forest.* The results are presented in Table 1.

The estimate reported in column (1), suggests that in areas where potential maize yields increased relatively more experienced a decrease in area covered with agricultural land. The level-estimate reported in column (10)[10] indicates that for municipalities experiencing a relatively larger increase in potential yields for maize, the average decrease in agricultural land cover was 13.36 square kilometres. This confirms the theory that land-augmenting technical change increases the land endowment, and decreases the need for land in production. The estimated effect on forest to agriculture transition reported in column (3) further consolidates this link, as these estimations indicate that areas with a higher increase in potential maize yield experienced insignificant effects on transition of land from forest to agriculture. These results suggest that adoption of land-augmenting technical change reduces the farmers need to expand production. The level-estimate, shown in column (11) provides even stronger evidence for this theory, as these results indicate that land-augmenting technical change can have the potential to reduce the conversion of forest to agriculture.

Further, estimates reported in column (5), indicate that areas where potential maize yields increased relatively more experienced an increase in area covered with forest. The level-estimate reported in column (10) indicates that for municipalities experiencing a higher increase in potential yields for maize, the average increase in forest cover was 27.11 square kilometres.

[10]When interpreting the reduced form level-estimates we use our more conservative estimates, namely those that include controls; *Initial forest* and *Frontier*.

Table 1 - The Effect of Technological Change on Agricultural Land Use and Forest
(Reduced Form Estimates)

	Δ log area agricultural land cover		Δ log area FA		Δ log area forest cover		Δ log area AF		Δ Area agricultural land cover		Δ Area FA		Δ Area forest cover		Δ Area AF	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
ΔA^{maize}	-0.091***	-0.080***	0.024	0.000	0.039***	0.046***	0.063***	0.055***	-14.281***	-13.366***	-3.119**	-2.835**	40.773***	27.114***	0.250***	0.248***
	(0.013)	(0.010)	(0.015)	(0.014)	(0.006)	(0.006)	(0.010)	(0.009)	(3.043)	(2.825)	(1.441)	(1.322)	(7.288)	(4.704)	(0.055)	(0.055)
ΔA^{soy}	0.121***	0.198***	0.051	0.183***	-0.128***	-0.132***	-0.048**	-0.004	47.393***	47.010***	7.627**	7.613**	-69.745***	-63.229***	-0.348***	-0.344***
	(0.036)	(0.032)	(0.032)	(0.032)	(0.015)	(0.014)	(0.019)	(0.018)	(7.304)	(7.119)	(3.505)	(3.427)	(13.939)	(10.452)	(0.101)	(0.101)
log initial forest		0.083***		0.212***		0.012***		0.072***								
		(0.011)		(0.013)		(0.002)		(0.005)								
Initial forest										0.003**		0.002**		-0.048***		0.000*
										(0.002)		(0.001)		(0.009)		(0.000)
Frontier		0.028		-0.034		-0.052***		-0.026		7.015		6.814***		-69.507***		0.141
		(0.032)		(0.029)		(0.009)		(0.017)		(5.501)		(2.437)		(17.062)		(0.097)
Observations	4255	4255	4255	4255	4255	4255	4255	4255	4255	4255	4255	4255	4255	4255	4255	4255
Adjusted R^2	0.085	0.216	0.007	0.161	0.097	0.130	0.024	0.080	0.020	0.044	0.002	0.027	0.005	0.372	0.010	0.011

Notes: Changes in dependent variables are calculated over the years 1996 and 2006 when the data source is the MapBiomas Cover database (columns 1, 2, 5, 6, 9, 10, 13 and 14), and over the years 1995 and 2005 when the data source is the MapBiomas Transition database (columns 3, 4, 7, 8, 11, 12, 15 and 16). Changes in explanatory variables are calculated over the years 1996 and 2006. The control variable frontier is a dummy variable indicating whether a municipality experienced increase in used agricultural land between 1996 and 2006. The variable initial forest is calculated as the total area covered with forest in 1991. The unit of observation is the municipality. Observations in column 1 and 2 are weighted by share of aggregate agricultural land cover in 1996. Observations in column 5 and 6 are weighted by share of aggregate forest cover in 1996. Robust standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

This suggests that the reduced demand for land in production, induced by land-augmenting technical change, leads to released croplands and reduced pressure on forest. Moreover, this potential relationship is further confirmed by the estimated effect on agriculture to forest transition. The regression reported in column (9) displays that in areas where maize yields increased relatively more experienced an increase in transition of land use from agriculture to forest. The level-estimate reported in column (16) indicates that for municipalities experiencing a relatively larger increase in potential yields for maize, the average conversion of agricultural land to forest was 0.25 square kilometres. In other words, this coefficient demonstrates that adoption of land-augmenting technical change not only has the potential to reduce the pressure on forest, but even allow for regrowth. All reported estimates remain stable when we include controls[11]. Plots with scattered residuals illustrating the correlation between the dependent variables and potential yields in maize can be found in Appendix A.8.

In the case of soy, estimates reported in column (1) indicate that areas where potential soy yields increased relatively more experienced an increase in area covered with agricultural land. The level-estimate reported in column (10) suggests that for municipalities experiencing a relatively larger increase in potential yields for maize, the average decrease in agricultural land cover was 47.01 square kilometres. This supports the theory that labor augmenting technical change causes less labor to be required per unit of land, in order to produce the same output-level. Hence, adoption of this technology releases labor, and causes demand for land in production of soy to increase. The estimated effect on forest to agriculture transition, reported in column (3), is insignificant. However, when we add controls the estimated coefficient suggests that adoption of labor-augmenting technical change increases the conversion of forest to agricultural land. This effect is further confirmed by the level-estimate, reported in column (12). This coefficient indicates that for municipalities experiencing a relatively larger increase in potential yields for soy, the average conversion of forest to agricultural land was 7.61 square kilometres.

Further, estimates reported in column (5), indicate that areas where potential soy yields increased relatively more experienced a decrease in area covered with forest. The level-estimate reported in column (10) indicate that for municipalities experiencing a higher increase in potential yields for soy experienced an average decrease in forest cover equal to 63.23 square kilometres. This result suggests that the increased demand for land in production, induced by labor-augmenting technical change, leads to an expansion in croplands used for soy cultivation, increasing the pressure on forest. Further, this suggests that GE soy is not only replacing other crops but also expands at the expense of forests. The effect on agriculture to forest transition, reported in column (7), further strengthens

[11]See column (2), (4), (6), (8), (10), (12), (14) and (16), Table 1

this link, as these estimations indicate that areas with a higher increase in potential soy yields, experienced negative effect on agriculture to forest transition. Consequently, this result suggest that adoption of labor-augmenting technical change has a negative effect on the conversion from agricultural land to forest. When adding controls, this effect becomes insignificant. However, the level-estimate, shown in column (15), indicates a negative link between labor-augmenting technical change and forest to agriculture transition. Thus, the estimated effect on agriculture to forest transition confirms the theory of labor-augmenting technical change causing cropland used for soy production to expand into forests. Except for the ones highlighted above, all estimated coefficients remain stable when including controls[12]. Plots with scattered residuals illustrating the correlation between the dependent variables and potential yields in soy can be found in Appendix A.8.

7.2 First-Stage Estimates

We continue our analysis by documenting the relationship between the increase in potential yields for soy and maize, and the actual change in the amount of agricultural land cultivated with GE soy and second season maize. More specifically, we estimate Equation 7 presented in Subsection 6.1. On account of using two different instruments, we estimate different versions of the first-stage equation in an attempt to isolate exogenous variation in the first-stage dependent variables. First, we regress the outcome of interest on the change in potential yield for that given crop only. Second, we expand this regression by including change in potential yield for both crops. The main goal of the first-stage is to investigate the assumption that the change in potential yields of a given crop can be used to predict the actual expansion in the area of agricultural land cultivated with that crop.

Estimates of the first-stage relationship between potential yields for maize and soy, and the change in agricultural land devoted to second season maize and GE soy, are presented in Table 2. Coefficients shown in column (1) indicate that an increase in potential yields in maize has a positive and significant effect on area planted with second season maize. However, estimates shown in column (3) display that these coefficients become negative when including change in potential yields in soy in the regression. Contrary to our assumption, this finding suggests that potential yields in maize cannot be used to predict expansion in second season maize.

[12] See column (2), (6), (10), (12), (14) and (16), Table 1

Table 2 - The Effect of Technological Change on Second Season Maize and GE Soy Expansion
(First-Stage Estimates)

	Δ log 2nd season maize area		Δ log 2nd season maize area		Δ log GE soy area		Δ log GE soy area		Δ 2nd season maize area		Δ 2nd season maize area		Δ GE soy area		Δ GE soy area	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
ΔA^{maize}	0.111***	0.111***	-0.233***	-0.235***			0.040*	0.045**	1.980***	2.494***	-12.447***	-11.701***			4.267***	4.518***
	(0.011)	(0.011)	(0.022)	(0.022)			(0.022)	(0.022)	(0.717)	(0.703)	(3.254)	(3.025)			(1.137)	(1.174)
ΔA^{soy}			0.922***	0.935***	0.531***	0.550***	0.461***	0.471***			38.651***	37.906***	16.554***	16.629***	9.118***	8.775***
			(0.057)	(0.059)	(0.033)	(0.033)	(0.044)	(0.045)			(8.496)	(8.244)	(2.308)	(2.320)	(1.583)	(1.552)
log initial forest		-0.005		0.030**		0.044***		0.043***								
		(0.015)		(0.015)		(0.012)		(0.012)								
Initial forest										0.002*		0.002*		0.000		0.000*
										(0.001)		(0.001)		(0.000)		(0.000)
Frontier		-0.049		-0.037		-0.320***		-0.326***		3.619		5.355		-7.507***		-8.197***
		(0.047)		(0.045)		(0.045)		(0.046)		(4.896)		(5.022)		(2.417)		(2.508)
Observations	3652	3652	3652	3652	3637	3637	3637	3637	3652	3652	3652	3652	3637	3637	3637	3637
Adjusted R^2	0.021	0.021	0.129	0.130	0.101	0.114	0.102	0.115	0.000	0.011	0.016	0.026	0.030	0.031	0.033	0.035

Notes: Notes: Changes in both dependent and explanatory variables are calculated over the years 1996 and 2006. The unit of observation is the municipality. The control variable frontier is a dummy variable indicating whether a municipality experienced increase in used agricultural land between 1996 and 2006. The variable initial forest is calculated as the total area covered with forest in 1991. Robust standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A possible explanation for this finding might be differences in the length of the rain season across Brazil. An important requirement for double cropping is a long rain season, because this makes farmers able to plant the first season early and to grow a second season by the end of the wet season (Pires et al., 2016). Consequently, suitability for double cropping is higher in some regions of Brazil. Maps in Appendix A.6 display accumulated rainfall across Brazil, and show that areas of the country dominated by long rain seasons correspond to the areas suitable for soy when using high technology, shown in Figure 8 in Subsection 5.2.1. In contrast, the areas that are characterized by short rain seasons, correspond to the areas suitable for maize when using high technology. This feature might explain we find no evidence of second season maize expanding in areas suitable for maize.

The regression reported in column (3) further indicates that change in potential yields in soy has a positive and significant effect on the area planted with second season maize. This result suggests that potential yields in soy is a better predictor of expansion in area cultivated with second season maize, than potential yields in maize. A possible interpretation of this relationship is that second season maize is exploited as a way of consolidating production of soy and maize, rather than as a technique to increase existing maize production. Economically, there might be many advantages of consolidation, e.g. diluted fixed cost and optimized use of machines, storage and labor. It does not seem unlikely that farmers cultivating soy in areas with long rain seasons, could benefit from introducing a second harvesting season of maize. This might explain we find evidence of second season maize expanding in areas suitable for soy. Panel B in Appendix A.9 plots land cultivated with second season maize against technical change in soy. The plot displays that a high increase in potential yields for soy is positively correlated with expansion in second season maize. Note that all estimates remain stable when we add controls[13].

Maps developed by USDA, shown in Appendix A.5, also adds to the theory of consolidation. The maps display crop production in tons at municipality level in Brazil, for first season maize, second season maize and soybeans (IBGE, 2016). Map A and B, crop production for first and second season maize, respectively, demonstrate that the highest concentrations of these two crops do not occur in the same areas. With regard to second season maize and soybean production, Map B and C display a high presence of these two crops in the same areas. Hence, the maps indicate that production development of a second season maize to a greater degree follow the same development pattern as soybean production, than as first season maize. This is further confirmed by Pires el al. (2016), who states that nearly 58% of the total area of harvested maize in Brazil in 2014 was planted as a

[13]see column (2), (4), (6), (8), (10), (12), (14) and (16), in Table 2

second crop after soy[14].

In the case of GE soy, estimates shown in column (5) indicate that change in potential yields in soy has a positive and significant effect on area planted with GE soy. Estimates in (7) column show that this coefficient remain stable when we include change in potential maize yields. Contrary to what we expected, the regression also indicates that potential yields in maize has a positive and significant effect on the area planted with GE soy. This is also illustrated in Panel C in Appendix A.9, which plots land cultivated with GE soy against technical change in maize. The plot displays that a high increase in potential yields for maize is positively correlated with expansion in GE soy. Note that all estimates remain stable when we add controls[15].

These results suggest that changes in potential yields in soy, might not be as accurate at predicting technical change in soy as first anticipated. Rather, the estimated coefficients indicate that potential yields in soy and maize both can be used to predict expansion of GE soy, and that GE soy is cultivated in areas suited for both soy and maize. Figure 8 in Subsection 5.2.1 illustrates that areas characterized by a high increase in potential soy yields to a great extent coincide with areas characterized by a high increase in potential maize yields. If double cropping of soy and maize made cultivation of traditional maize relatively less profitable expansion of GE soy into these areas seems like a plausible consequence. Consequently, the positive effect of potential yields in maize on GE soy could indicate a substitution of traditional maize cultivation by soy cultivation. This can also be emphasized by the overall development in maize production from 1996 to 2006. As displayed in Panel E Figure 2 in Subsection 3.2.2, total area planted with maize has been quite stable, with increasing trends for second season maize cultivation, and declining trends for first season maize.

Based on the theory of substitution, an interesting extension is to include first season maize in the analysis. If the introduction of a second harvesting season of maize affected the cultivation of first season maize, it is possible that changes in first season maize cultivation also affect our reduced form estimates. Consequently, an analysis investigating the relationship between potential soy and maize yields and first season maize can be found in Appendix A.4. Table 7 suggests a positive relationship between an increase in potential yields for maize and first season maize. These regressions motivate the theory that development in first season maize cultivation plays a part in the observed effects of potential yields in maize in the reduced form estimations. Further, these findings also

[14] In an effort to further motivate this link, we also estimated the model including an interaction term of GE soy and second season maize. However, the F-statics of these estimations are all below 10. Consequently, including this interaction cannot be used to support our theory.

[15] see column (2), (4), (6), (8), (10), (12), (14) and (16), in Table 2

comply with the hypothesis that a second harvesting season for maize contributes to increased consolidation between soy and maize production. Our reduced form results can be interpreted as a signal that the cultivation of traditional maize is in decline, and can be explained by economics of scope. If double cropping of soy and maize enabled soybean farmers to produce maize more effectively, and at a lower cost than farmers cultivating traditional maize, it seems reasonable to assume that these farmers would struggle. Consequently, a possible decrease in traditional maize cultivation can be explained by increased double cropping of soy and maize.

Regardless of these complex results, the first-stage estimates still indicate that the potential yields are relevant to explain expansion in second season maize and GE soy. Consequently, we conclude that potential yields can be used as instruments in the second stage regressions.

7.3 Instrumental Variables Estimates

We continue the analysis by estimating the 2SLS regressions. More specifically, we estimate Equation 9 presented in Section 6.1. The dependent variable, Δy_j, is the change in the four different land use outcomes; *Agricultural land cover*, *Transition of land from forest to agriculture*, *Forest cover*, and *Transition of land from agriculture to forest.* The explanatory variables are the instrumented change in agricultural land devoted to second season maize and GE soy. The estimated results are presented in Table 3.

The estimated coefficient of a change in area cultivated with second season maize on agricultural land cover, is significant and positive. More specifically, the result in column (1) indicates that a 1% increase in the area cultivated with second season maize leads to a 0.06% increase in agricultural land cover. This estimated positive effect supports the theory of consolidation between soy and maize, presented in Subsection 7.2, as it may reflect that second season maize is used as a way of jointly cultivating soy and maize in areas that experienced a relatively larger increase in potential yields for soy.

For the agriculture to forest transition variable, the estimated effect of a change in area cultivated with second season maize is insignificant at a 5% level, shown in column (3) and (4). However, the level-model, shown in column (11), supports the finding that second season maize induce an expansion of agricultural land. Consequently, the estimated relationship strengthen the theory of this cultivation technique being exploited mainly as a way consolidating soy and maize cultivation.

Table 3 - The Effect of Technological Change on Agricultural Land Use and Forest
(2SLS Estimates)

	log-log model								level-level model							
	Δ log area agricultural land cover		Δ log area FA		Δ log area forest cover		Δ log area AF		Δ Area agricultural land cover		Δ Area FA		Δ Area forest cover		Δ Area AF	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Δ log 2nd season maize area	0.060***	0.071***	-0.026	0.097*	-0.105*	-0.231	-0.178***	-0.135***								
	(0.014)	(0.011)	(0.054)	(0.050)	(0.061)	(0.252)	(0.039)	(0.037)								
Δ log GE soy area	-0.041**	-0.003	0.245***	0.294***	0.120	0.382	0.351***	0.359***								
	(0.020)	(0.012)	(0.066)	(0.060)	(0.110)	(0.502)	(0.055)	(0.052)								
Δ 2nd season maize area									1.520***	1.512***	0.271***	0.264***	-2.872***	-2.299***	-0.016***	-0.015***
									(0.203)	(0.200)	(0.086)	(0.084)	(0.596)	(0.466)	(0.005)	(0.005)
Δ log GE soy area									0.087	0.111	-0.117**	-0.087**	3.030***	1.277***	0.022***	0.023***
									(0.151)	(0.146)	(0.046)	(0.041)	(0.781)	(0.455)	(0.006)	(0.006)
log initial forest		0.047***		0.198***		0.024		0.061***								
		(0.012)		(0.012)		(0.024)		(0.006)								
Initial forest										0.001		0.001**		-0.044***		0.000**
										(0.001)		(0.000)		(0.010)		(0.000)
Frontier		-0.008		0.052		0.072		0.074***		0.758		4.990***		-49.913***		0.373***
		(0.042)		(0.032)		(0.141)		(0.024)		(4.918)		(1.430)		(16.354)		(0.130)
Observations	4223	4223	4223	4223	4223	4223	4223	4223	4223	4223	4223	4223	4223	4223	4223	4223
F-test of instrument (GE-soy)	37.99	58.65	114.99	119.31	21.13	12.51	114.99	119.31	27.54	27.67	27.54	27.67	27.54	27.67	27.54	27.67
F-test of instrument (2nd maize)	44.54	70.49	194.22	192.84	18.51	15.90	194.22	192.84	15.53	15.35	15.53	15.35	15.53	15.35	15.53	15.35

Notes: Changes in dependent variables are calculated over the years 1996 and 2006 when the data source is the MapBiomas Cover database (columns 1, 2, 5, 6, 9, 10, 13 and 14), and over the years 1995 and 2005 when the data source is the MapBiomas Transition database (columns 3, 4, 7, 8, 11, 12, 15 and 16). Changes in explanatory variables are calculated over the years 1996 and 2006. The control variable frontier is a dummy variable indicating whether a municipality experienced increase in used agricultural land between 1996 and 2006. The variable initial forest is calculated as the total area covered with forest in 1991. The unit of observation is the municipality. Observations in column 1 and 2 are weighted by share of aggregate agricultural land cover in 1996. Observations in column 5 and 6 are weighted by share of aggregate forest cover in 1996. Robust standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The estimated coefficients of a change in area cultivated with second season maize on forest cover, reported in column (5) and (6), are insignificant at a 5% level. However, the results of the level-level model, reported in column (13), indicate that if a municipality experienced an increase in the area cultivated with second season maize by 1 square kilometre, forest cover would decrease by almost 2.9 square kilometres. This quite substantial effect could reflect that an expansion of double cropping of soy and maize also requires enlarged infrastructure. Hence, this negative effect supports the theory of consolidation between soy and maize, as the estimated coefficient is likely to reflect the effect of joint cultivation of soy and maize expanding into forests. A negative relationship between second season maize and agriculture to forest transition, shown in column (7), further supplements this theory.

Note that the estimated coefficients, besides from the one ones discussed, remain stable when we include controls[16]. With regard to the F-statistics, the instruments for both explanatory variables in the level-level model and log-log model meet the Staiger and Stock (1994) criterion of an F-statistic above 10.

The divergence in results between the log-log model and the level-level model, especially with regard to changes in forest cover, can be explained by the use of log transformed variables. As shown in the figures in Appendix A.7, log transforming change in forest cover makes it evident that the distribution of positive and negative observations of change in forest cover are relatively even. Thus, this transformation scales down the effect of the most extreme municipalities in terms of change in forest cover between 1996 and 2006.

The estimated coefficient of a change in area cultivated with GE soy on agricultural land cover, shown in column (1), is negative. More specifically, the estimate indicates that a 1% increase in the area cultivated with GE soy leads to a 0.04% decrease in agricultural land cover. However, when including controls, as shown in column (2), the estimated effect is not significant. The results of the level-model, reported in column (9) and (10), further demonstrate an insignificant effect of a GE soy expansion on agricultural land cover. These results are in line with the first-stage estimations, indicating that GE soy also expanded into areas suitable for maize, possibly into areas originally cultivated with first season maize. Consequently, the estimated insignificant effect can be explained by GE soy expanding into areas already covered with agricultural activities.

For the *Forest to agriculture transition* variable, the estimated effect of GE soy is ambiguous. On one hand, the results of the log-log model, indicate a positive relationship between expansion in GE soy and forest to agriculture transition. On the other hand, the results

[16]See column (2), (8), (10), (12), (14) and (16), Table 3

from the level-level model, shown in column (11), support the theories presented in Subsection 7.2, and further also the estimated effect of GE soy presented in column (1). More specifically, a negative relationship between GE soy expansion and forest to agriculture transition motivates the link between reduced cultivation of first season maize and double cropping. First, by double cropping of maize and soy induces a decline in first season maize cultivation. Second, by this decline having a negative effect on agricultural land use, in spite of an expansion of GE soy in these areas.

The estimated effect of a change in area cultivated with GE soy on forest cover is insignificant at a 5% level, shown in column (5) and (6). However, the level-level model indicates that an expansion in area cultivated with GE soy leads to an increase in forest cover. More specifically, the results reported in column (13) indicate that if a municipality experienced an increase in the area cultivated with GE soy by 1 square kilometre, forest cover would increase by approximately 3 square kilometres. A quite high effect, that can be explained by GE soy also expanding into areas formerly cultivated with traditional maize. A decline in the cultivation of first season maize releases croplands and enables GE soy cultivation to expand into these areas rather than into forests. A positive relationship between GE soy and agriculture to forest transition, shown in column (7), further enhances this link. Quite surprisingly, the results suggest that, despite an expansion of GE soy into areas originally covered with first season maize, the decline in traditional maize cultivation has allowed forest to grow back on previously cultivated land. This result supports the evidence that land-augmenting technical change has the potential to induce regrowth of forests. However, they also indicate that this occurs indirectly through second season maize replacing traditional cultivation of maize.

Note that, apart for the ones discussed, the estimated coefficients remain stable when we add control variables[17]. With regard to the F-statistics for both instrumented variables, all estimates reported in Table 3 meet the Staiger and Stock (1994) criterion of an F-statistic above 10.

7.4 Heterogeneity Analysis

As shown in the in maps illustrating crop production, in Appendix A.5, soy and maize cultivation are dominating in some regions. This also becomes evident when looking at Figure 8 in Subsection 5.2.1, as this illustrate that some areas of Brazil are highly suited for soy and maize cultivation, whilst others are not. Due to these differences, some regions may drive the result presented in the main analysis, whilst other regions might

[17]See column (4), (8), (10), (12), (14) and (16), Table 3

contribute to our regressions being underestimated. Accordingly, it could be interesting to examine whether we can find evidence of heterogeneity within our main sample. However, as discussed in section 6.3 our identification hinges on these differences in potential yields as a source of cross-sectional variation in the intensity of treatment. As a consequence, estimating our analysis on subgroups of our main sample might affect the validity of the results. Nevertheless, the results of a heterogeneity analysis of different subgroups, the five Brazilian regions; North Region, North East Region, South East Region, South Region and Central-West Region, can be found in Appendix A.11.

7.5 Summary of the Results

Taken together, our empirical results do provide evidence for our predictions presented in Subsection 4.4, suggesting that land augmenting technical change has a positive effect on agricultural land use and a negative effect on forest. The opposite counts for labor-augmenting technical change. However, our analysis reveals that the observed effects are more complex than the theories forming the base of our predictions.

The empirical findings from the reduced form estimations are consistent with the predictions of our model presented in Subsection 4.4. The regressions suggest that when technical change in agriculture is land-augmenting, it increases the land endowment. This leads to a decline in the farmers need to expand production, and reduces the pressure on forests. In contrast, we find that when technical change is labor-augmenting and strongly labor-saving, it causes farmers to expand production and increases the pressure on forests.

The results from first-stage regressions provide useful information. Most importantly, contrary to the assumption of Bustos et al. (2016), our results suggest that changes in potential yields, when switching to the high technology, do not perform adequately with regard to predicting an expansion in crop-specific technical change in soy and maize. We find that a second harvesting season in maize expands in areas suitable for this cultivation technique, and that these areas are not the ones characterized by a high increase in potential yields for maize. Further, our results suggests that double cropping increases the profitability of GE soy relative to traditional maize cultivation, causing GE soy to expand both in areas suited for soy and maize. Hence, the first-stage regressions suggest that change in potential yields for maize seems to be qualified to predict expansion in GE soy, as change in potential yields for soy. Moreover, we also find change in penitential yields for soy to be the sole predictor of expansion in second season maize. In other words, the expansion of the two crops seem to be closer related than first anticipated. We also find that our empirical results reflect the observed development in consolidation of GE soy and second season maize.

The estimated coefficients from the 2SLS regressions are complex. However, these regressions support our findings and discussions from the first-stage analysis. First, that the observed effects of land-augmenting technical change occurs indirectly, due to double cropping between maize and soy provoking a decline in traditional maize cultivation. Second, that the positive relationship between labor-augmenting technical change and agricultural land cover, can be observed through the expansion of joint cultivation of soy and second season maize.

8 Discussion

In the following section, we discuss possible shortcomings of the dataset and the limitations imposed on our study as a result of our chosen estimation strategy. Finally, we conduct a short discussion on the external validity of our results.

8.1 Limitations to the Dataset

As mentioned in Section 6.7, we assume the variable of second season maize to be 0 in 1996. As farmers in Brazil started to exploit the idea of a second harvesting season of maize in the 1980s, this assumption might be incorrect. Consequently, the measured changes in area reaped with second season maize in our dataset might be higher than the true value. Thus, we also run the risk of wrongly estimating the effect of the introduction of a second harvesting season of maize. However, as discussed in Subsection 3.2.2, the area devoted to second season maize only started to expand in the 1990s. This supports the assumption that area reaped with second season maize might be close to 0 in 1996.

Another drawback of our dataset is the limited variation seen in our explanatory variables. Even if the number of observations in the first-stage regressions for GE soy and second season maize are 4223 and 4240, observations different from zero are only 503 and 891, respectively. Thus, the cross sectional variation in our instrumented variables is scarce. As increased variation in the explanatory variables raises the likelihood of pinning down the accurate relationship between the explanatory variables and the dependent variables, the opposite increases the possibility of inaccuracy in our estimates (Wooldridge, 2016). This problem becomes particularly evident when looking at scatterplots of our first-stage regressions, presented in Appendix A.9. As displayed in all panels, a great amount of the observations are centered around zero.

Lastly, it is important to emphasize the fact that the MapBiomas datasets on land cover and land transition are pre-processed statistics of Collection 3. The final version of Collection 3 is due to be launched in the end of 2018. As the extent of the potential corrections is unknown, we cannot be completely confident that it does not exist any lacks or inaccuracies in the dataset. The reasoning for using the pre-processed version of Collection 3.0, and not Collection 2.3, is that the dataset contains observations dated back to as early as 1985, contrary to the Collection 2.3 dataset which ranges from 2000 to 2010.

8.2 Limitations to the Estimation Strategy

At least four potential problems with the estimation strategy can be identified. First of all, we can never guarantee that the instruments themselves are not correlated with the error term. If they are, the independence assumption would be violated and our results would be biased. However, as argued in Subsection 6.3, we have confidence that this restriction is fulfilled.

Second, although the instruments are strong when estimating the expansion of GE soy and second season maize in the baseline sample, the strong relationship does not always hold when using *Second season maize area share* and *GE soy area share* as instrumented variables. This analysis is shown in Appendix A.3. As shown in Appendix A.11, weak instruments are further a problem in the heterogeneity analysis when using smaller samples, e.g. for the North and North East regions. As mentioned in Subsection 6.1 weak instruments can lead to inconsistency and bias in the IV estimates. Consequently, 2SLS estimations might produce misleading estimates of statistical significance when utilizing weak instruments, even with large sample sizes (Murray, 2006). We cannot rule out the possibility that there exists other instrumental variables that would have performed better. Additionally, obtaining resembling results using alternative instruments would increase the credibility of our IV estimates (Murray, 2006) Consequently, a potential topic for further studies would be to look into possible alternative instruments.

Third, in Section 6 we assumed that a high increase in potential yields for a given crop should be a strong predictor of the actual expansion in area of agricultural land cultivated with that particular crop between 1996 and 2006. However, as we find evidence that the expansions of the two crops are closely related, our results indicate that this assumption only partly holds. This poses problems, as it makes it harder to isolate, and interpret, the effect of an expansion in one crop specifically. A possible improvement of our model could be to investigate other factor-biased technologies, not as closely related as those studied in this thesis. However, this is beyond the scope of this thesis and rather an interesting topic for further research.

Lastly, models including multiple endogenous variables are complex and can be hard to handle. Despite the fact that we have access to two seemingly good instruments, we cannot be certain that we are able to tackle the two causal questions at the same time (J. D. Angrist & Pischke, 2018). Consequently, our 2SLS estimates can be difficult to interpret, and an economic interpretation of the results must be done with vigilance.

8.3 External Validity

Central to any study is the extent to which the results are generalizable, more specifically the external validity. It is possible that the estimated effects from Brazil are not directly transferable to other countries. As mentioned in Subsection 3.1.1, Brazil sustains 40% of the world's remaining tropical forest. Consequently, the country is particularly vulnerable to deforestation. Logically, a country without any forests will not be exposed to deforestation regardless of an expansion in the area cultivated with agricultural crops. Thus, it is possible that the estimated effects found in this study are not directly transferable to other countries, sustaining less, or other types, of forests. Further, the effect of increased technical progress in agriculture also depends on the country's dependence of the agricultural sector, and our results are not necessarily generalizable to all countries. However, countries with large agricultural sectors could potentially experience similar effects of increased agriculture productivity. Based on this discussion, it would be interesting to analyze whether similar results could be obtained studying other countries.

9 Concluding Remarks

This thesis aims to provide empirical evidence of the effect of agricultural productivity, in the form of factor-biased technical change, on agricultural land use and forests in Brazil. In order to find evidence in favour of, or against, the predicted effects, we have used an instrumental variable approach, combining a reduced form estimation with a two-stage least squares estimation. We study the introduction of genetically engineered soy seeds and second season maize, exploiting the different impacts of these technologies on potential crop yields across Brazil from 1996 to 2006.

In an effort to track changes in agricultural land use and how these affect forests, we utilize newly digitized data on land cover and land transition from MapBiomas for the whole of Brazil. We combine this data with data from the agricultural census and PAM database, released by the IBGE, as well as en exogenous measure of technological change from the FAO-GAEZ database.

The results imply that when technical change in agriculture is land-augmenting, as in the case of second season maize, it increases the land endowment and reduces the pressure on forests. Further, we even find evidence that this technology has the potential to induce regrowth of forest. Interestingly, our results indicate that these effects does not occur directly through second season maize, as first anticipated. Rather, we find evidence that second season maize primarily is exploited as a method to consolidate soy and maize cultivation. Our results suggest that the expansion of second season maize does not occur independently of GE soy, as first anticipated. Consequently, we find the effects of land-augmenting technical change to be indirect, as a result of increased double cropping of soy and maize leading to a reduction in traditional maize cultivation. In contrast, we find that when technical change is labor-augmenting and strongly labor-saving, as in the case of GE soy expansion, it increases the pressure on forests. However, our estimations suggest that this effect occurs as a combination of increased double cropping between second season maize and GE soy, as well as GE soy expanding into areas originally cultivated with first season maize.

By exploiting data on the whole of Brazil, this thesis contributes to prior research on the relationship between agricultural productivity and forest loss. Our results do to some degree support the findings of Assunção et al. (2016), indicating ambiguous effects of increased agricultural productivity. We argue that these effects to some extent depend on the factor-bias of technical change. However, we also find evidence that these effects are more closely related than first anticipated. Consequently, our findings provide insight regarding the debate of the effect of agricultural productivity on deforestation.

Finally, as agricultural activities is one of the main causes of deforestation and severe forest degradation (WWF, 2018), our results can have implications for current policies aiming to hamper or reverse forest loss. Taken together, our findings imply that investing in research on new agricultural technologies may have positive effects on deforestation, and even lead to regrowth of forest. Consequently, our results suggest that investments in technological development within agriculture, can be an effective measure in the fight against deforestation.

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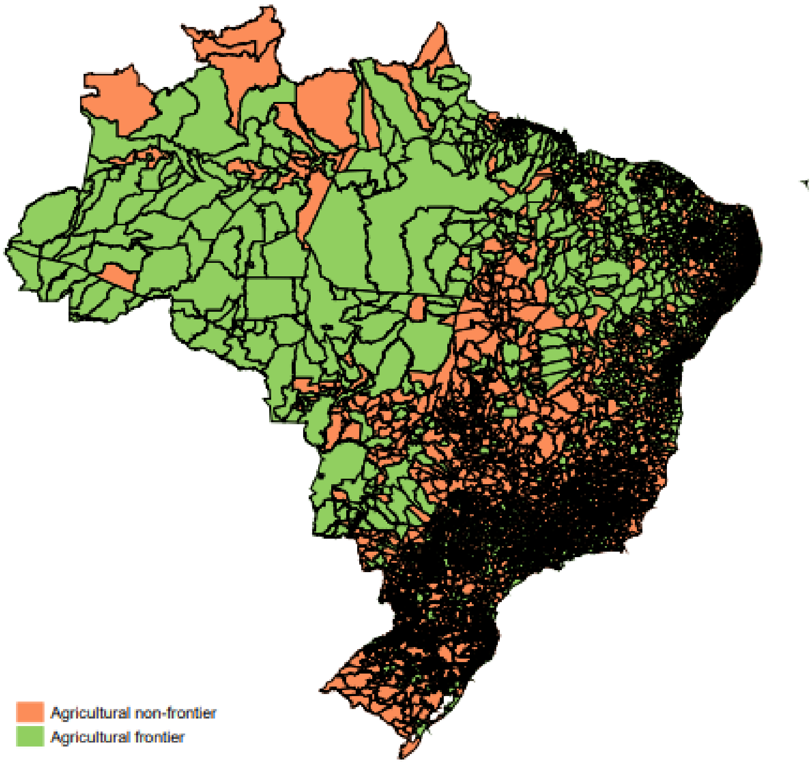
A Appendix

A.1 Mabiomas Classes

Level 1	**Level 2**	**Level 3**
1. Forest	1.1 Natural Forest	1.1.1 Forest Formation 1.1.1 Forest Formation 1.1.2. Savanna Formation
2. Non-Forest Natural Formation	2.1. Wetland 2.2. Grassland Formation 2.3. Salt flat 2.4. Other non forest natural formation	
3. Farming	3.1. Pasture 3.2. Agriculture	3.2.1. Annual and Perennial Agriculture 3.2.2. Semi-Perennial Agriculture
4. Other non-vegeted area	4.1. Beach and Dune 4.2. Urban Infrastructure 4.3. Rocky outcrop 4.4. Mining 4.5. Other non vegetated area	
5. Water Bodies	5.1. River, Lake and Ocean 5.2. Aquaculture	
6. Non Observed		

A.2 Agricultural Frontier Municipalities



Notes: Created by Bustos et al. (2016) Source: Bustos, Caprettini, & Ponticelli, 2018, Online Appendix. Based on data from Brazilian Agricultural Censuses of 1996 and 2006 (IBGE, 1996 IBGE, 2006).

A.3 Instrumented Variables as Share of Agricultural Land

Similarly to Bustos et al., we estimate our regressions using share of agricultural land devoted to the different crops as our instrumented variables. More specifically, the variables are calculated area reaped with GE soy or second season maize divided by total land in farms. The share of agricultural land devoted to each crop are informative about the cultivation of GE soy and second season maize in agriculture, relative to other crops. Thus, these variables can provide useful insight into how crop specific technical change affects the composition of crops in agriculture, and how a change in this composition might affect land use.

The first-stage and 2SLS regressions can be found in Table 4 and Table 5. The 2SLS estimations display that when estimating the our model using share of GE soy and second season maize as the instrumented variables, the estimated F-statistics, with regard to second season maize, are below, or only slightly above, 10, indicating that the instruments are weak. A weak instrument is a signal that one should be careful to interpret the results of this model (Staiger & Stock, 1994). Thus, we refrain from drawing any conclusion from these regressions, but keep them in for transparency reasons.

Table 4 - The Effect of Technological Change on Second Season Maize Area Share and GE Soy Expansion Area Share *(First-Stage Estimates)*

	Δ 2nd season maize area share				Δ GE soy area share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔA^{maize}	0.007***	0.008***	-0.012***	-0.012***			0.008***	0.008***
	(0.002)	(0.002)	(0.004)	(0.004)			(0.001)	(0.001)
ΔA^{soy}			0.053***	0.054***	0.019***	0.018***	0.006***	0.004***
			(0.011)	(0.012)	(0.002)	(0.002)	(0.001)	(0.001)
log initial forest		0.000		0.003		-0.002***		-0.002***
		(0.002)		(0.002)		(0.000)		(0.000)
Frontier		-0.021***		-0.021***		-0.005**		-0.006**
		(0.007)		(0.007)		(0.002)		(0.002)
Observations	4240	4240	4240	4240	4055	4055	4055	4055
Adjusted R^2	0.002	0.004	0.014	0.015	0.049	0.053	0.062	0.068

Notes: Changes in both dependent and explanatory variables are calculated over the years 1996 and 2006. The unit of observation is the municipality. The control variable frontier is a dummy variable indicating whether a municipality experienced increase in used agricultural land between 1996 and 2006. The variable initial forest is calculated as the total area covered with forest in 1991. Robust standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5 - The Effect of Technological Change on Agricultural Land Use and Forest
(2SLS Estimates: Instrumented Variables as Share of Agricultural Land)

	Δ log area agricultural land cover		Δ log area FA		Δ log area forest cover		Δ log area AF	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ 2nd maize area share	0.376**	0.454***	0.325	2.561***	-0.680**	-0.801***	-1.794***	-0.831*
	(0.154)	(0.172)	(0.717)	(0.859)	(0.265)	(0.306)	(0.640)	(0.466)
Δ GE soy area share	-0.988***	-0.314	4.514***	5.253***	2.302	6.116**	6.078***	6.462***
	(0.319)	(0.284)	(1.178)	(1.202)	(1.578)	(2.623)	(1.070)	(1.039)
log initial forest		0.046***		0.205***		0.014***		0.090***
		(0.012)		(0.013)		(0.005)		(0.007)
Frontier		0.098**		0.056		-0.028**		-0.003
		(0.048)		(0.035)		(0.012)		(0.025)
Observations	4055	4055	4055	4055	4055	4055	4055	4055
Adjusted R^2	-0.516	-0.610	-0.096	-0.370	-0.965	-1.835	-1.411	-0.777

Notes: Changes in dependent variables are calculated over the years 1996 and 2006 (column 1, 2, 5 and 6) and over the years 1995 and 2005 (column 3, 4, 7 and 8). Changes in explanatory variables are calculated over the years 1996 and 2006. The unit of observation is the municipality. The control variable frontier is a dummy variable indicating whether a municipality experienced increase in used agricultural land between 1996 and 2006. The variable initial forest is calculated as the total area covered with forest in 1991. The reported statistics are the F statistic from the first-stage regression as well as the number of observations. Robust standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.4 The Effect of Change in Potential Yields on First Season Maize

In this appendix subsection we aim to motivate the theory that first season maize plays a part in the observed effects of potential yields in maize in the reduced form estimation. Including first season maize in our first-stage regressions enables us to examine whether we can find empirical proof of our theory that joint cultivation between GE soy and second season maize causes a decrease in cultivation of first season maize.

As discussed in subsection 6.7, data separating between first- and second harvesting seasons of maize are only available from 2003 onward. However, because we assume that the area cultivated with second season maize was 0 in 1996, we further argue that the level of first season maize equals the observed level of all maize cultivated in 1996. This assumption allows us to investigate the effect of potential yields in soy and maize on change in area cultivated with first season maize.

The results investigating the relationship between first season maize and potential yields are reported in Table 6. The estimate effects on *log first season maize area*, shown in column (1) and (2), indicate no significant effect of potential yields. For the level-estimate the estimated effect on a change in potential yields in maize becomes positive when change in potential yields in soy is included in the regression, shown in column (4). In contrast, the estimated effect of potential yields in soy is negative. The positive relationship between a change in potential yields in maize and first season maize indicate that potential yields in maize serve as a good predictor of an changes in area cultivated with first season maize. In contrast, the negative effect of potential yields in soy indicate that this does not serve as a good predictor. With respect to the all estimated effects on *log first season maize area share* are insignificant.

Consequently, the results do provide some indications that a change in potential yields in maize can predict changes in first season maize cultivation. This strengthens the theory that the observed effect of changes in potential yields in maize in the reduced form estimations in part stem from changes in the area cultivated with first season maize.

All estimates remain stable when we include controls, as shown in Table 7. The only exception is the effect of change in potential yields in maize of the regression in column (3). However, when including controls, the estimated effect becomes significant.

Table 6 - The Effect of Technological Change on First Season Maize Expansion *(First-Stage Estimates)*

	Δ log 1st season maize area		Δ 1st season maize area		Δ 1st season maize area share	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔA^{maize}	0.002	0.002	0.414	2.202***	0.000***	0.000***
	(0.009)	(0.017)	(0.252)	(0.583)	(0.000)	(0.000)
ΔA^{soy}		-0.002		-4.779***		-0.000***
		(0.038)		(1.486)		(0.000)
Observations	3568	3568	3568	3568	3567	3567
Adjusted R^2	-0.000	-0.001	0.000	0.005	0.002	0.006

Notes: Changes in both dependent and explanatory variables are calculated over the years 1996 and 2006. The unit of observation is the municipality. The control variable frontier is a dummy variable indicating whether a municipality experienced increase in used agricultural land between 1996 and 2006. The variable initial forest is calculated as the total area covered with forest in 1991. Robust standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

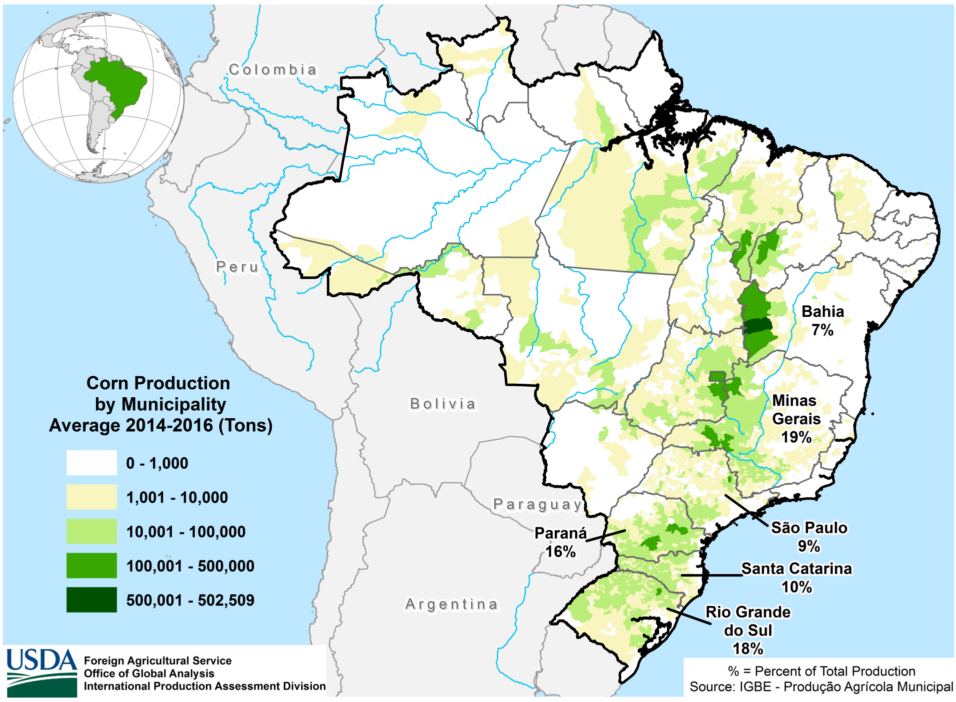
Table 7 - The Effect of Technological Change on First Season Maize Expansion *(First-Stage Estimates with Controls)*

	Δ log 1st season maize area		Δ 1st season maize area		Δ 1st season maize area share	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔA^{maize}	0.012	-0.002	0.578**	2.484***	0.000**	0.000***
	(0.009)	(0.016)	(0.252)	(0.575)	(0.000)	(0.000)
ΔA^{soy}		0.036		-5.073***		-0.000***
		(0.038)		(1.472)		(0.000)
log initial forest	0.080***	0.081***			-0.000***	-0.000***
	(0.010)	(0.010)			(0.000)	(0.000)
Initial forest			0.001***	0.000665***		
			(0.000)	(0.000)		
Frontier	-0.077**	-0.076**	1.665	1.411	-0.000***	-0.000***
	(0.038)	(0.038)	(1.130)	(1.112)	(0.000)	(0.000)
Observations	3568	3568	3568	3568	3567	3567
Adjusted R^2	0.026	0.031	0.018	0.018	0.057	0.067

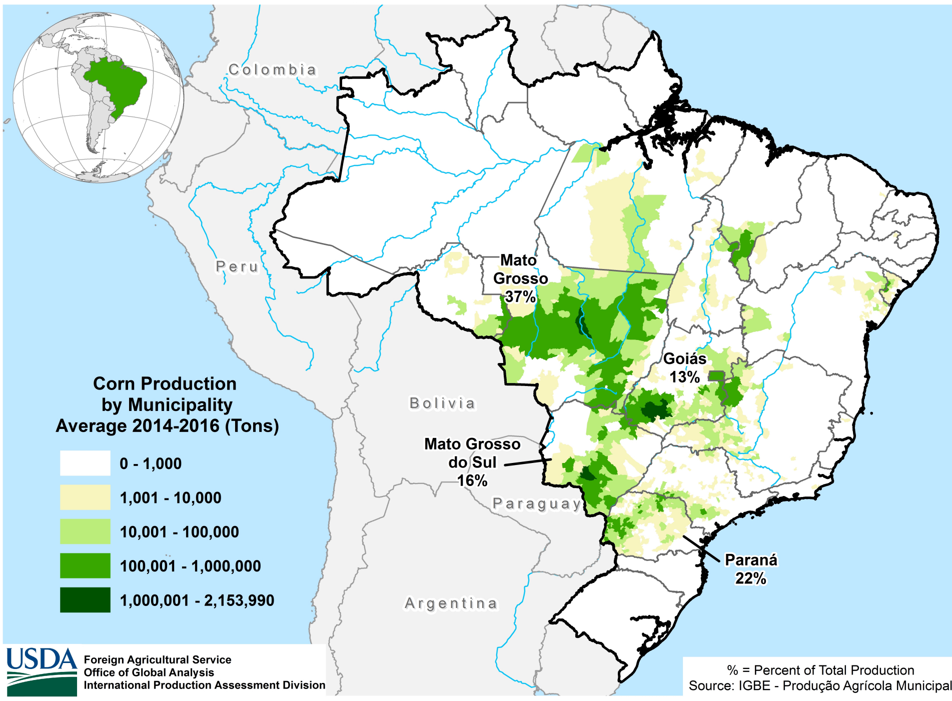
Notes: Changes in both dependent and explanatory variables are calculated over the years 1996 and 2006. The unit of observation is the municipality. The control variable frontier is a dummy variable indicating whether a municipality experienced increase in used agricultural land between 1996 and 2006. The variable initial forest is calculated as the total area covered with forest in 1991. Robust standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.5 Crop Production in Brazil

MAP A. First Season Maize Production

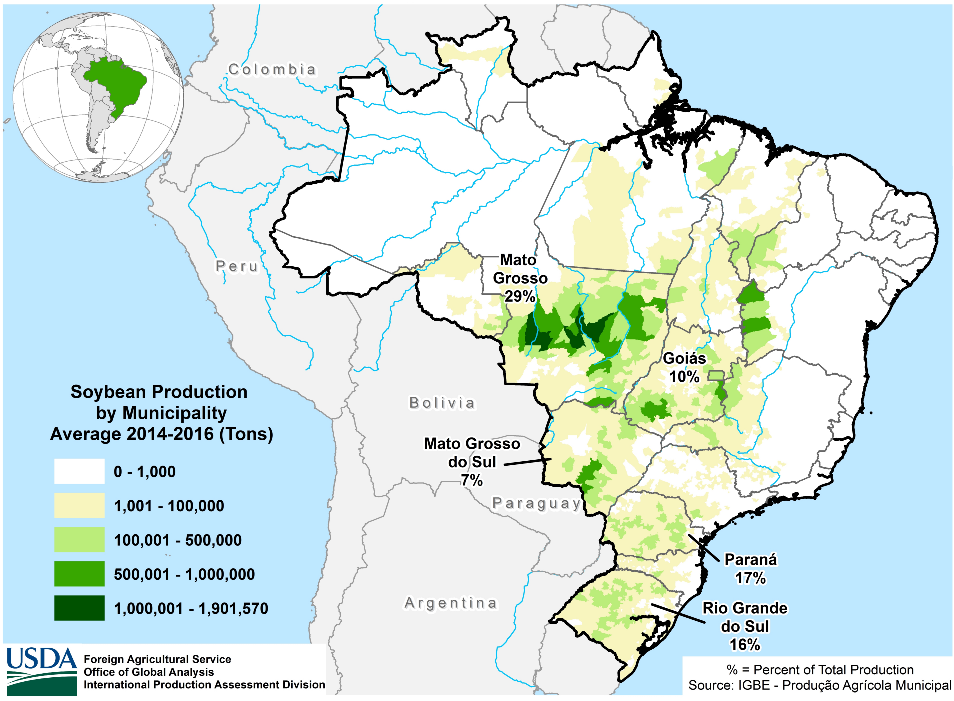


MAP B. Second Season Maize Production



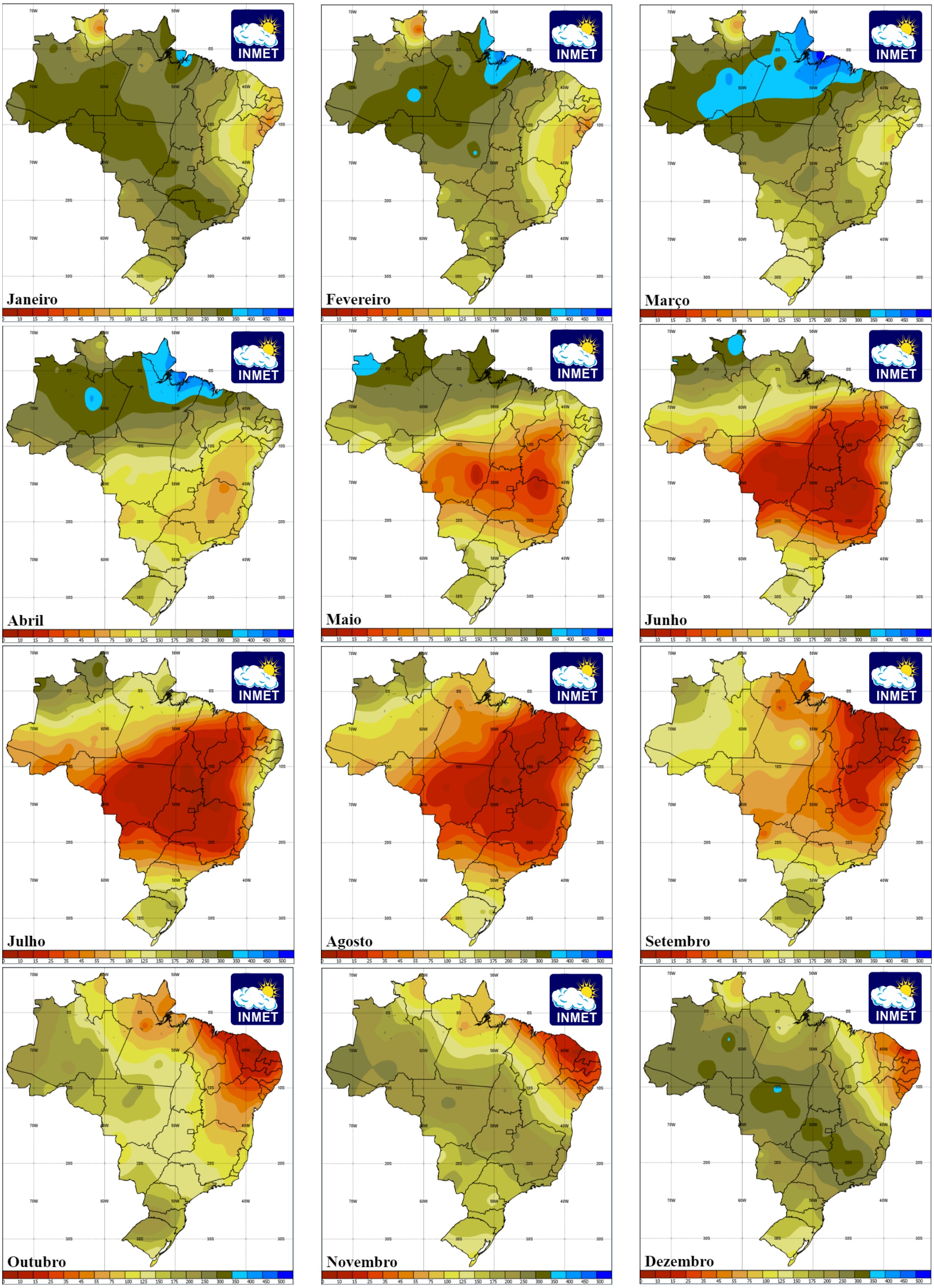
Notes: The maps illustrate production in tons at municipality level in Brazil, average for the period 2014 to 2026. The data source is IBGE PAM (2016), and the maps have been developed by USDA Foreign Agriculture Service (2018).

MAP C. Soybean Production



Notes: The maps illustrate production in tons at municipality level in Brazil, average for the period 2014 to 2026. The data source is IBGE PAM (2016), and the maps have been developed by USDA Foreign Agriculture Service (2018).

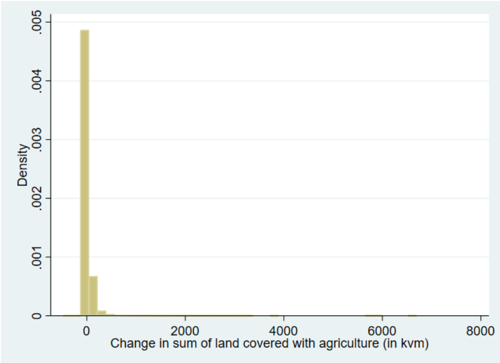
A.6 Accumulated Rainfall in Brazil



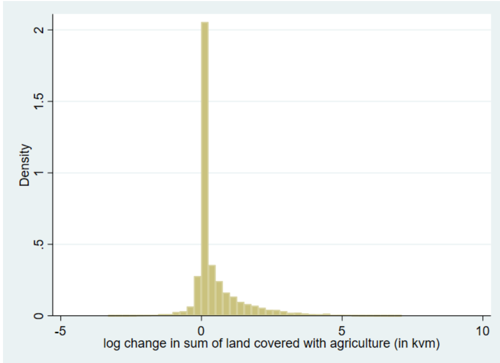
Notes: The maps illustrate accumulated rainfall in Brazil on a monthly basis, and are based on data collected from 1981 to 2010. The scale indicates accumulated rainfall in mm from low(red) to high(blue). The maps have been developed by the Brazilian Institute of Meteorology (INMET, 2018).

A.7 Density of Observations

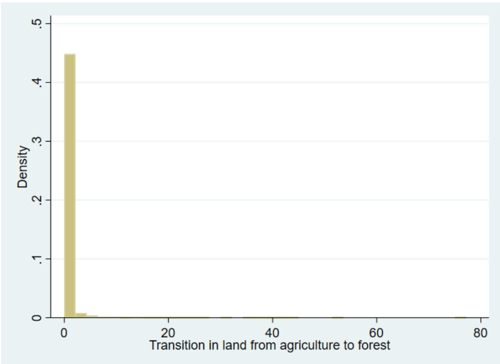
PANEL A. Agricultural Land Cover



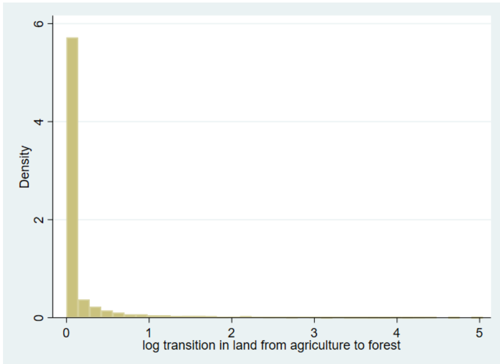
PANEL B. Log Agricultural Land Cover



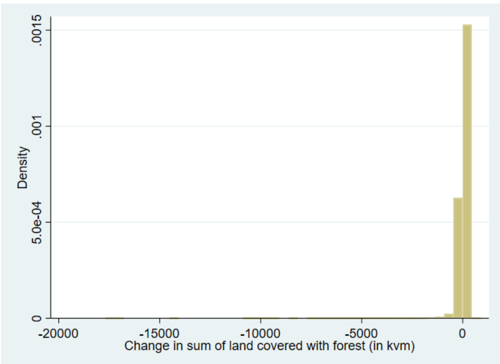
PANEL C. Transition of Land from Forest to Agriculture



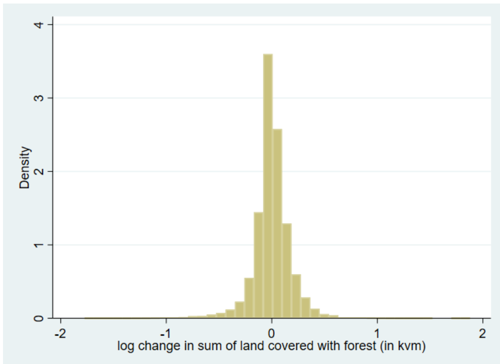
PANEL D. Log transition of Land from Forest to Agriculture



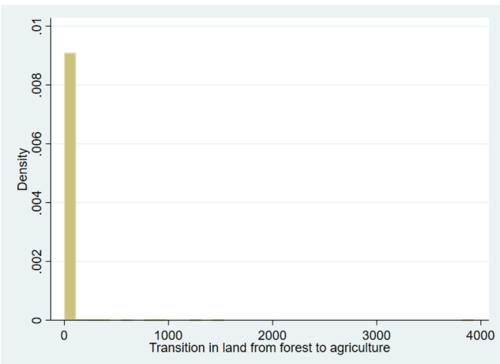
PANEL E. Forest Cover



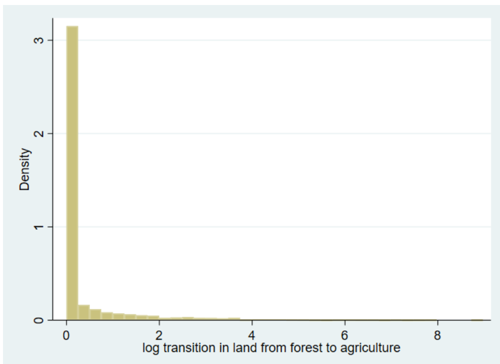
PANEL F. Log Forest Cover



PANEL G. Transition of land from Agriculture to Forest

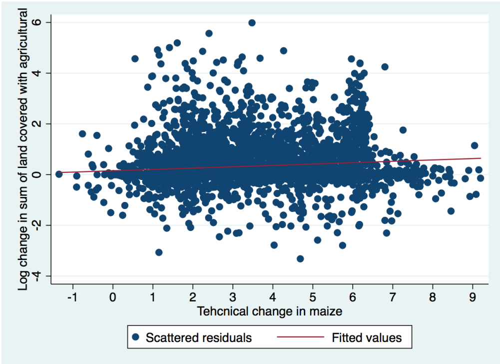


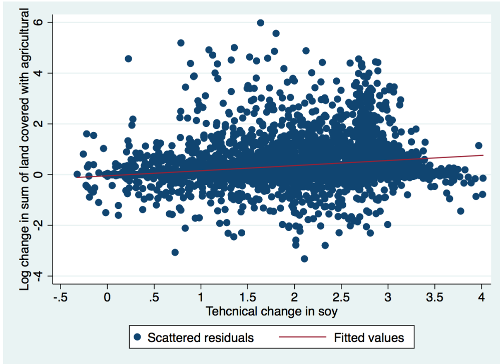
PANEL H. Log Transition of land from Agriculture to Forest



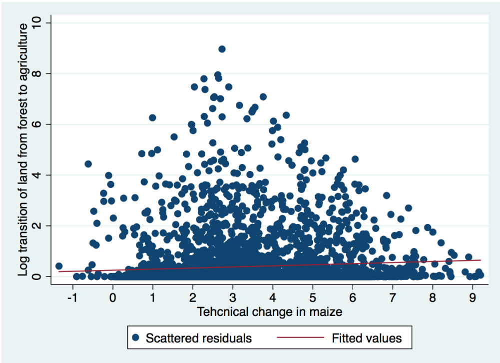
A.8 Reduced Form Scatter Plots

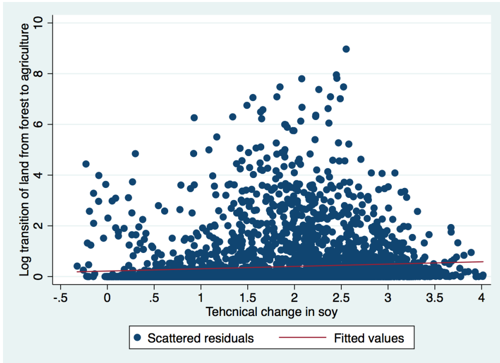
PANEL A. Log Agricultural Land Cover and Potential Yields in Maize (Soy) left (right)



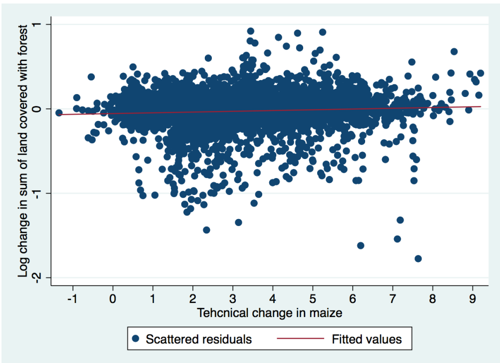


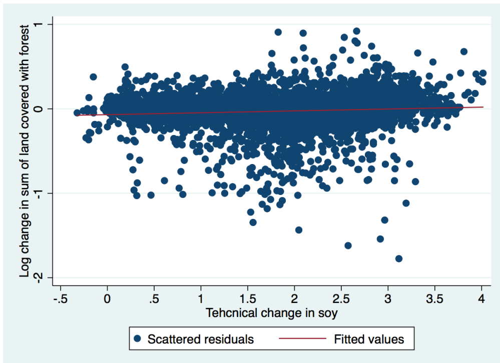
PANEL B. Log Transition of Land from Forest to Agriculture and Potential Yields in Maize (Soy) left (right)



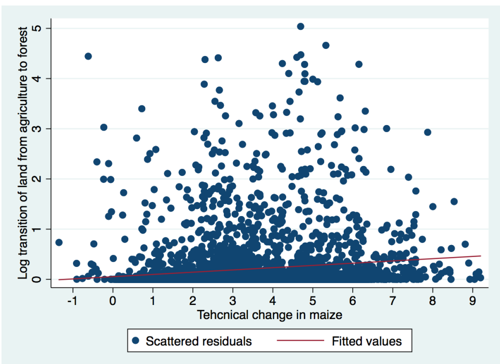


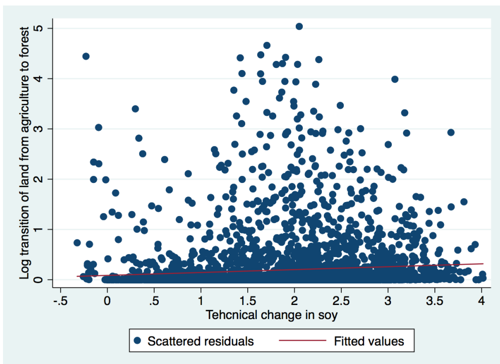
PANEL C. Forest Cover and Potential Yields in Maize (Soy) left (right)





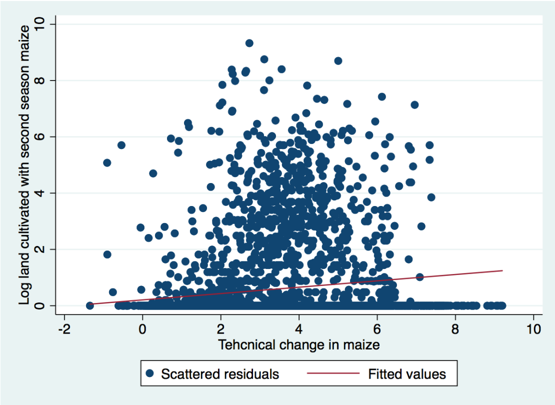
PANEL D. Log Transition of land from Agriculture to Forest and Potential Yields in Maize (soy) left (right)



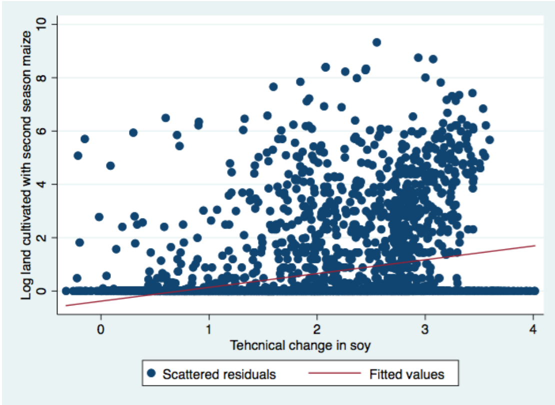


A.9 First-Stage Scatter Plots

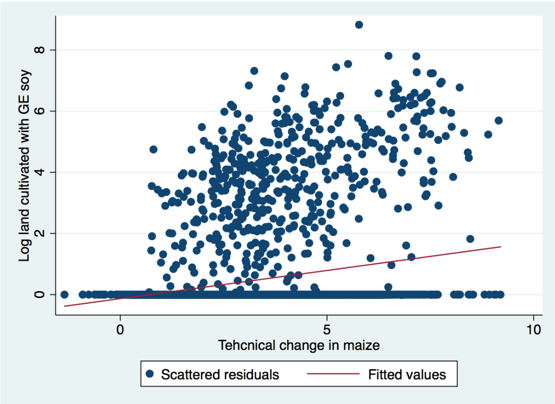
PANEL A. Second Season Maize and Potential Yields in Maize



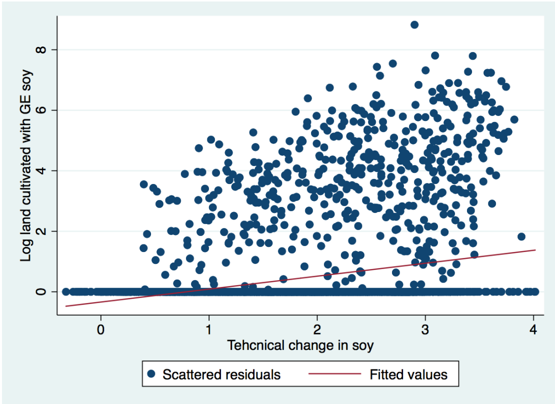
PANEL B. Second Season Maize and Potential Yields in Soy



PANEL C. GE Soy and Potential Yields in Maize



PANEL D. GE Soy and Potential Yields in Soy



A.10 Data

This part of the appendix contains a detailed description of the main variables used in the empirical analysis.

Agricultural Land Cover: Data on agricultural land cover come from MapBiomas Project map statistics database (MapBiomas, 2018a). The variable is defined as the area, measured in square kilometres, covered with agricultural activities. The variable is calculated by summing the two sub-classes of the level 2 class Agriculture: Annual and perennial agriculture and Semi-Perennial Agriculture. All variables come at the municipality level and have been aggregated at the at the level of AMC using the correspondence used by Bustos et al. (2016), proposed by IPEA and IBGE. First differences are defined between 1996 and 2006.

Log Agricultural Land Cover: The variable is defined as the logarithm of the variable *Agricultural Land Cover*.

Transition of Land From Forest to Agricultural Land: Data on forest to agriculture transition cover come from MapBiomas Project map statistics database (MapBiomas, 2018a). The variable is defined as the amount of area, measured in square kilometres, covered with forest in 1995, which were transformed to areas covered with agriculture land by 2005. To calculate total transition between sub-classes of Natural forest and Agriculture, we use the same approach as described for *Agricultural Land Cover* and *Forest Cover*. All variables come at the municipality level and have been aggregated at the at the level of AMC using the correspondence used by Bustos et al. (2016), proposed by IPEA and IBGE[18].

Log Transition of Land From Forest to Agriculture: The variable is defined as the logarithm of the variable *Transition of Land From Forest to Agriculture*.

Forest Cover: Data on forest cover come from MapBiomas Project map statistics database (MapBiomas, 2018a). The variable is defined as the area, measured in square kilometres, covered with forest. The variable is calculated by summing up three sub-classes of the level 2 class Natural forest: Forest formation, Savanna formation and Mangrove. All variables come at the municipality level and have been aggregated at the at the level of AMC using the correspondence used by Bustos et al. (2016), proposed by IPEA and IBGE. First differences are defined between 1996 and 2006.

[18]The variables *Transition of land from forest to agriculture* and *Transition of land from agriculture to forest* demonstrate explicit information about areas covered with forest (agriculture) in 1995, which were converted into areas covered with agriculture (forest) land by 2005. Consequently, because these variables measure transitions of land they are in themselves first-differences

Log Forest Cover: The variable is defined as the logarithm of the variable *Forest Cover.*

Transition of Land From Agriculture to Forest: Data on forest to agriculture transition come from MapBiomas Project map statistics database (MapBiomas, 2018a). The variable is defined as the amount of area, measured in square kilometres, covered with agricultural land in 1995, which were transformed to areas covered with forest by 2005. To calculate total transition between sub-classes of Natural forest and Agriculture, we use the same approach as described for *Agricultural Land Cover* and *Forest Cover.* All variables come at the municipality level and have been aggregated at the at the level of AMC using the correspondence used by Bustos et al. (2016), proposed by IPEA and IBGE[19].

Log Transition of Land From Forest to Agriculture: The variable is defined as the logarithm of the variable *Transition of Land From Agriculture to Forest.*

Change in potential soy (maize) yield: Data on potential soy (maize) yield come from the dataset constructed by Bustos et al. (2016). The original source is the FAO GAEZ v3.0 database (FAO & IIASA, 2018b). The variables are constructed in two main steps. First through the use of two variables from the *Sustainability and Potential Yield* Series: *Total production capacity for low input level rain-fed soybean (maize)* and *Total production capacity for high input level rain-fed soybean (maize)*, i.e. potential yields in soy(maize) using low ans high inputs. Second, these variables are used in order to capture *potential production capacity in terms of output density which equals total grid cell production potential divided by grid cell area* (Bustos et al., 2018). More specifically, the variable *Change in Potential Soy (Maize) Yield* is calculated by subtracting the low input level variable from the high input level variable in each municipality. Both variables are measured in tons per hectare. All data is aggregated at the AMC-level (Bustos et al., 2018).

Low-level inputs are describes as follows: *"Under a low level of inputs (traditional management assumption), the farming system is largely subsistence based. Production is based on the use of traditional cultivars (if improved cultivars are used, they are treated in the same way as local cultivars), labor intensive techniques, and no application of nutrients, no use of chemicals for pest and disease control and minimum conservation measures"*. Whilst high level inputs have the following description: *"under a high level of input (advanced management assumption), the farming system is mainly market oriented. Commercial production is a management objective. Production is based on improved or*

[19]The variables *Transition of land from forest to agriculture* and *Transition of land from agriculture to forest* demonstrate explicit information about areas covered with forest (agriculture) in 1995, which were converted into areas covered with agriculture (forest) land by 2005. Consequently, because these variables measure transitions of land they are in themselves first-differences

high yielding varieties, is fully mechanized with low labor intensity and uses optimum applications of nutrients and chemical pest, disease and weed control"(FAO & IIASA, 2018c).

Agricultural Land Cultivated with Second Season Maize: Data on agricultural land cultivated with second season maize come from the Produção Agrícola Municipal (PAM) database (IBGE, 2016). The variable is defined as area reaped with second season maize, measured in square kilometres. The data on area reaped with second season maize in 2006 has been obtained from table 839; *Área plantada, área colhida, quantidade produzida e rendimento médio de milho, 1ª e 2ª safras* and it is assumed to be 0 in 1996. All variables come at the municipality level and have been aggregated at the at the level of AMC using the correspondence used by Bustos et al. (2016), proposed by IPEA and IBGE. First differences are defined between 1996 and 2006.

Log Agricultural Land Cultivated with Second Season Maize: The variable is defined as the logarithm of the variable *Agricultural Land Cultivated with Second Season Maize.*

Share of Agricultural Land Cultivated with Second Season Maize: The variable is defined as *Agricultural Land Cultivated with Second Season Maize* divided by total land in farms. Total land in farms in 2006 has been obtained from the agricultural census and table 787; *número de estabelecimentos e área dos estabelecimentos agropecuários, por condição legal do produtor em relação ás terras, sexo do produtor, grupos de atividade econômica e grupos de área total.* Variables on total land in farms come at the municipality level and have been aggregated at the at the level of AMC using the correspondence used by Bustos et al. (2016), proposed by IPEA and IBGE. First differences are defined between 1996 and 2006.

Agricultural Land Cultivated with First Season Maize: Data on agricultural land cultivated with first season maize come from the Produção Agrícola Municipal (PAM) database (IBGE, 2016). The variable is defined as area reaped with first season maize, measured in square kilometres. The data on area reaped with first season maize in 2006 has been obtained from table 839; *Área plantada, área colhida, quantidade produzida e rendimento médio de milho, 1ª e 2ª safras* and it is assumed to be equal to area reaped with traditional maize in 1996. All variables come at the municipality level and have been aggregated at the at the level of AMC using the correspondence from Bustos et al. (2016), proposed by IPEA and IBGE. First differences are defined between 1996 and 2006.

Log Agricultural Land Cultivated with First Season Maize: The variable is defined as the logarithm of the variable *Agricultural Land Cultivated with First Season Maize*.

Share of Agricultural Land Cultivated with First Season Maize: The variable is defined as *Agricultural Land Cultivated with First Season Maize* divided by total land in farms. Total land in farms in 1996 has been obtained from the Agricultural Census table 314 (*área dos estabelecimentos por grupo de actividade econômica e condição legal das terras*) in 1996 (IBGE, 1996) and table 787 (*número de estabelecimentos e área dos estabelecimentos agropecuários, por condição legal do produtor em relação ás terras, sexo do produtor, grupos de atividade econômica e grupos de área total*) in 2006 (IBGE, 2006). All variables come at the municipality level and have been aggregated at the at the level of AMC using the correspondence used by Bustos et al. (2016), proposed by IPEA and IBGE. First differences are defined between 1996 and 2006.

Agricultural Land Cultivated with Genetically Engineered Soy: Data on agricultural land cultivated with genetically engineered soy come from the Agricultural Census (IBGE, 2006). The variable is defined as area reaped with genetically engineered soy, measured in square kilometres. The data on area reaped with genetically engineered soy in 2006 has been obtained from table 824; (*ção, venda, valor da produção e área colhida da lavoura temporária por produtos da lavoura temporária, tipo de semente, tipo de colheita, tipo de cultivo e destino da produção*) and it is assumed to be 0 in 1996. All variables come at the municipality level and have been aggregated at the at the level of AMC using the correspondence used by Bustos et al. (2016), proposed by IPEA and IBGE. First differences are defined between 1996 and 2006.

Log Agricultural Land Cultivated with Genetically Engineered Soy: The variable is defined as the logarithm of the variable *Agricultural Land Cultivated with Genetically Engineered Soy*.

Share of Agricultural Land Cultivated with Genetically Engineered Soy: The variable share of agricultural land cultivated with GE soy comes from the dataset constructed by Bustos et al. (2016). The original source is the 2006 Agricultural Census (IBGE, 2006). The variable is defined as area reaped with genetically engineered soy divided by total land in farms, and has been aggregated to AMC-level (Bustos et al., 2018). First differences are defined between 1996 and 2006.

Initial Forest: Area of initial forest comes from MapBiomas MapBiomas, 2018a. The variable is calculated as the total area covered with forest in 1991, measured in square kilometres. We define forest in the same manner as the variable *Forest Cover*. All variables come at the municipality level and have been aggregated at the at the level of AMC using the correspondence used by Bustos et al. (2016), proposed by IPEA and IBGE.

Log Initial Forest: The variable is defined as the logarithm of the variable *Initial*

Forest.

Agricultural Frontier: The variable *Agricultural Frontier* comes from the dataset developed by Bustos et al. (2016). The variable is equal to 1 if an AMC is defined as an agricultural frontier and 0 otherwise. Frontier municipalities is defined as those which experienced an increase in land use for agricultural activities between 1996 and 2006. For an overview of frontier and non-frontier municipalities, please refer to Appendix A.2.

A.11 Heterogenity Analysis

In this subsection of the Appendix we perform a heterogeneity analysis of different subgroups of our main sample. More specifically, we test whether the effect of technological change differs between the Brazilian regions. As discussed in section 3, soy and maize cultivation are dominating in some regions. Accordingly, due to differences across Brazil, some regions may drive the result from our baseline regression. This subsection presents the regression of the heterogeneity analysis, running our main equation for the five Brazilian regions; North Region, North East Region, South East Region, South Region and Central-West Region. A complete overview of the Brazilian states in the different regions can be found in the table below.

With regard to the North and the North East region, none of the estimated coefficients for GE soy and second season maize are significant for any of the four outcomes of interest. This can be explained by the fact that both GE soy and second season maize production are close to non existent in these regions, relative to the South East, South and Central-West regions, as illustrated in Figure A.5 in Appendix. Further, the F-statistics demonstrate that potential yields for soy and maize should be considered as weak instruments.

In the case of the South East Region, the South Region and the Central-West Region, some of the regressions yield an F-statistic above 10 for both instrumented variables. However, in most of the regressions the estimated F-statistics, are below, or only slightly above, 10, indicating that the instruments are weak. Consequently, we cannot draw any solid conclusions from these regressions.

North:	**North East:**	**Central-West:**	**South East:**	**South:**
Amazonas	Maranhão	Mato Grosso	São Paulo	Paraná
Roraima	Piauí	Mato Grosso do Sul	Rio de Janeiro	Rio Grande do Sul
Amapá	Ceará	Goiás	Espírito Santo	Santa Catarina
Pará	Rio Grande do Norte	Distrito Federal	Minas Gerais	
Tocantins	Pernambuco			
Rondônia	Paraíba			
Acre	Sergipe			
	Alagoas			
	Bahia			

Table 8 - North Region: Forest Cover and FA Transition
(*Second Stage Regression*)

	Δ Forest Cover				Δ FA	
	Area	log area	log area	Area	log area	log area
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Area GE soy	52.829			13.479		
	(438.606)			(13.213)		
Δ Area 2nd maize	0.000			0.000		
	(.)			(.)		
Δ GE soy area share		-347.258			852.774	
		(256.164)			(777.023)	
Δ 2nd maize area share		0.000			0.000	
		(.)			(.)	
Δ log area GE soy			-0.686			1.687
			(0.499)			(1.552)
Δ log area 2nd maize			0.000			0.000
			(.)			(.)
Observations	253	250	253	253	250	253
F-test of instruments (GE soy)	1.15	1.30	1.36	1.15	1.30	1.36
F-test of instruments (2nd maize)	-	-	-	-	-	-
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Changes for Forest Cover in both dependent and explanatory variables are calculated over the years 1996 and 2006. Changes for Transition FA in both dependent and explanatory variables are calculated over the years 1995 and 2005. The unit of observation is the municipality. The control variable frontier is a dummy variable indicating whether a municipality experienced increase in used agricultural land between 1996 and 2006. The variable initial forest is calculated as the total area covered with forest in 1991. Robust standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9 - North Region: Agricultural Land Cover and AF Transition
(*Second Stage Regression*)

	Δ Agricultural Cover				Δ AF	
	Area	log area	log area	Area	log area	log area
	(1)	(2)	(3)	(4)	(5)	(6)
Δ GE soy area		11.828			-0.098	
	(27.673)			(0.106)		
Δ 2nd maize area	0.000			0.000		
	(.)			(.)		
Δ GE soy area share		2462.948*			-138.262	
		(1462.547)			(141.638)	
Δ 2nd maize area share		0.000			0.000	
		(.)			(.)	
		(0.033)	(0.035)		(0.004)	(0.004)
Δ log GE soy area			5.612*			-0.282
			(3.243)			(0.284)
Δ log 2nd maize area			0.000			0.000
			(.)			(.)
Observations	253	250	253	253	250	253
F-test of instruments (GE soy)	1.15	1.30	1.36	1.15	1.30	1.36
F-test of instruments (2nd maize)	-0.500	-	-	-	-	-
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Changes for Agricultural Cover in both dependent and explanatory variables are calculated over the years 1996 and 2006. Changes for Transition Agriculture to Forest in dependent variables are calculated over the years 1995 and 2005. The unit of observation is the municipality. The control variable frontier is a dummy variable indicating whether a municipality experienced increase in used agricultural land between 1996 and 2006. The variable initial forest is calculated as the total area covered with forest in 1991. Robust standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10 - North East Region: Forest Cover and FA Transition
(*Second Stage Regression*)

	Δ Forest Cover			Δ FA		
	Area	log area	log area	Area	log area	log area
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Area GE soy	-204.437			-2.374		
	(146.165)			(6.473)		
Δ Area 2nd maize	-43.573			-1.466		
	(46.802)			(1.841)		
Δ GE soy area share		-2566.657			-16931.881	
		(1724.787)			(17477.585)	
Δ 2nd maize area share		1.520			335.170	
		(61.085)			(788.266)	
Δ log area GE soy			-3.348			-31.960
			(3.506)			(35.117)
Δ log area 2nd maize			-0.353			4.850
			(0.977)			(10.148)
Observations	1445	1435	1445	1445	1435	1445
F-test of instruments (GE soy)	1.90	2.03	2.31	1.90	2.03	2.31
F-test of instruments (2nd maize)	1.13	0.32	2.10	1.13	0.32	2.10
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Changes for Forest Cover in both dependent and explanatory variables are calculated over the years 1996 and 2006. Changes for Transition FA in both dependent and explanatory variables are calculated over the years 1995 and 2005. The unit of observation is the municipality. The control variable frontier is a dummy variable indicating whether a municipality experienced increase in used agricultural land between 1996 and 2006. The variable initial forest is calculated as the total area covered with forest in 1991. Robust standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11 - North East Region: Agricultural Land Cover and AF Transition
(*Second Stage Regression*)

	Δ Agricultural Cover			Δ AF		
	Area	log area	log area	Area	log area	log area
	(1)	(2)	(3)	(4)	(5)	(6)
Δ GE soy area	5.105			-6.980		
	(16.958)			(4.749)		
Δ 2nd season maize area	-6.382			-1.537		
	(6.465)			(1.595)		
Δ GE soy area share		-860.426			-13910.877	
		(3583.366)			(15011.612)	
Δ 2nd season maize area share		77.431			304.335	
		(169.400)			(693.025)	
Δ log GE soy area			-3.946			-27.536
			(8.884)			(30.647)
Δ log 2nd season maize area			1.688			4.683
			(2.745)			(9.024)
Observations	1445	1435	1445	1445	1435	1445
F-test of instruments (GE soy)	1.90	2.03	2.31	1.90	2.03	2.31
F-test of instruments (2nd maize)	1.13	0.32	2.10	1.13	0.32	2.10
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Changes for Agricultural Cover in both dependent and explanatory variables are calculated over the years 1996 and 2006. Changes for Transition Agriculture to Forest in dependent variables are calculated over the years 1995 and 2005. The unit of observation is the municipality. The control variable frontier is a dummy variable indicating whether a municipality experienced increase in used agricultural land between 1996 and 2006. The variable initial forest is calculated as the total area covered with forest in 1991. Robust standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12 - South East Region: Forest Cover and FA Transition
(*Second Stage Regression*)

	Δ Forest Cover			Δ Transition FA		
	Area	log area	log area	Area	log area	log area
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Area GE soy	1.568			0.454***		
	(1.816)			(0.149)		
Δ Area 2nd maize	-0.703*			0.026		
	(0.414)			(0.024)		
Δ GE soy area share		-51.050			107.705	
		(31.264)			(121.091)	
Δ 2nd maize area share		3.519**			5.890	
		(1.672)			(5.553)	
Δ log area GE soy			-0.132			1.588***
			(0.105)			(0.470)
Δ log area 2nd maize			0.073**			0.044
			(0.029)			(0.114)
Observations	1393	1359	1393	1393	1359	1393
F-test of instruments (GE soy)	6.30	5.78	15.17	6.30	5.78	15.17
F-test of instruments (2nd maize)	12.97	13.94	71.50	12.97	13.94	71.50
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Changes for Forest Cover in both dependent and explanatory variables are calculated over the years 1996 and 2006. Changes for Transition FA in both dependent and explanatory variables are calculated over the years 1995 and 2005. The unit of observation is the municipality. The control variable frontier is a dummy variable indicating whether a municipality experienced increase in used agricultural land between 1996 and 2006. The variable initial forest is calculated as the total area covered with forest in 1991. Robust standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13 - South East Region: Agricultural Land Cover and AF Transition
(*Second Stage Regression*)

	Δ Agricultural Cover			Δ AF		
	Area	log area	log area	Area	log area	log area
	(1)	(2)	(3)	(4)	(5)	(6)
Δ GE soy area	-3.345			0.143**		
	(3.673)			(0.070)		
Δ 2nd season maize area	5.290***			0.005		
	(1.095)			(0.007)		
Δ GE soy area share		-1875.820**			117.889*	
		(830.683)			(66.676)	
Δ 2nd season maize area share		117.496***			-0.484	
		(44.100)			(2.827)	
Δ log GE soy area			-6.105***			1.143***
			(2.333)			(0.361)
Δ log 2nd season maize area			2.558***			-0.073
			(0.583)			(0.081)
Observations	1393	1359	1393	1393	1359	1393
F-test of instruments (GE soy)	6.30	5.78	15.17	6.30	5.78	15.17
F-test of instruments (2nd maize)	12.97	13.94	71.50	12.97	13.94	71.50
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Changes for Agricultural Cover in both dependent and explanatory variables are calculated over the years 1996 and 2006. Changes for Transition Agriculture to Forest in dependent variables are calculated over the years 1995 and 2005. The unit of observation is the municipality. The control variable frontier is a dummy variable indicating whether a municipality experienced increase in used agricultural land between 1996 and 2006. The variable initial forest is calculated as the total area covered with forest in 1991. Robust standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 14 - South Region: Forest Cover and FA Transition
(*Second Stage Regression*)

	Δ Forest Cover			Δ FA		
	Area	log area	log area	Area	log area	log area
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Area GE soy	0.078***			0.002**		
	(0.025)			(0.001)		
Δ Area 2nd maize	0.014			0.011***		
	(0.041)			(0.004)		
Δ GE soy area share		0.290***			0.857**	
		(0.108)			(0.353)	
Δ 2nd maize area share		0.258**			1.561**	
		(0.124)			(0.753)	
Δ log area GE soy			0.023***			0.075***
			(0.006)			(0.015)
Δ log area 2nd maize			0.018***			0.116***
			(0.005)			(0.021)
Observations	779	702	779	779	702	779
F-test of instruments (GE soy)	24.64	40.53	90.14	24.64	40.53	90.14
F-test of instruments (2nd maize)	12.58	2.88	186.64	12.58	2.88	186.64
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Changes for Forest Cover in both dependent and explanatory variables are calculated over the years 1996 and 2006. Changes for Transition FA in both dependent and explanatory variables are calculated over the years 1995 and 2005. The unit of observation is the municipality. The control variable frontier is a dummy variable indicating whether a municipality experienced increase in used agricultural land between 1996 and 2006. The variable initial forest is calculated as the total area covered with forest in 1991. Robust standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 15 - South Region: Agricultural Land Cover and AF Transition
(*Second Stage Regression*)

	Δ Agricultural Cover			Δ AF		
	Area	log area	log area	Area	log area	log area
	(1)	(2)	(3)	(4)	(5)	(6)
Δ GE soy area share	0.151*			0.002**		
	(0.092)			(0.001)		
Δ 2nd season maize area	0.829***			0.001		
	(0.262)			(0.001)		
Δ GE soy area share		-1.633***			0.964***	
		(0.451)			(0.295)	
Δ 2nd season maize area share		1.511**			0.829**	
		(0.753)			(0.401)	
Δ log GE soy area			-0.076***			0.071***
			(0.019)			(0.015)
Δ log 2nd season maize area			0.162***			0.059***
			(0.029)			(0.013)
Observations	779	702	779	779	702	779
F-test of instruments (GE soy)	24.64	40.53	90.14	24.64	40.53	90.14
F-test of instruments (2nd maize)	12.58	2.88	186.64	12.58	2.88	186.64
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Changes for Agricultural Cover in both dependent and explanatory variables are calculated over the years 1996 and 2006. Changes for Transition Agriculture to Forest in dependent variables are calculated over the years 1995 and 2005. The unit of observation is the municipality. The control variable frontier is a dummy variable indicating whether a municipality experienced increase in used agricultural land between 1996 and 2006. The variable initial forest is calculated as the total area covered with forest in 1991. Robust standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 16 - Central-West Region: Forest Cover and FA Transition
(*Second Stage Regression*)

	Δ Forest Cover			Δ FA		
	Area	log area	log area	Area	log area	log area
	(1)	(2)	(3)	(4)	(5)	(6)
Δ GE soy Area	6.303			-2.976**		
	(4.473)			(1.487)		
Δ 2nd maize Area	-1.560*			0.942***		
	(0.937)			(0.274)		
Δ GE soy area share		-2.565			-118.537**	
		(5.322)			(50.794)	
Δ 2nd maize area share		0.531			14.761**	
		(0.427)			(5.755)	
Δ log GE soy area			0.779			27.808
			(3.187)			(113.810)
Δ log 2nd maize area			-0.475			-17.509
			(2.052)			(73.306)
Observations	353	309	353	353	309	353
F-test of instruments (GE soy)	6.35	13.70	22.58	6.35	13.70	22.58
F-test of instruments (2nd maize)	5.11	3.37	42.70	5.11	3.37	42.70
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Changes for Forest Cover in both dependent and explanatory variables are calculated over the years 1996 and 2006. Changes for Transition FA in both dependent and explanatory variables are calculated over the years 1995 and 2005. The unit of observation is the municipality. The control variable frontier is a dummy variable indicating whether a municipality experienced increase in used agricultural land between 1996 and 2006. The variable initial forest is calculated as the total area covered with forest in 1991. Robust standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 17 - Central-West Region: Agricultural Land Cover and AF Transition
(*Second Stage Regression*)

	Δ Agricultural Cover			Δ AF		
	Area	log area	log area	Area	log area	log area
	(1)	(2)	(3)	(4)	(5)	(6)
Δ GE soy area	-5.026			-0.007		
	(3.798)			(0.017)		
Δ 2nd season maize area	2.344***			0.007		
	(0.801)			(0.004)		
Δ GE soy area share		-108.899**			-4.574	
		(50.881)			(13.837)	
Δ 2nd season maize area share		10.536**			2.799**	
		(4.871)			(1.257)	
Δ log GE Soy area			20.177			4.821
			(82.848)			(19.289)
Δ log 2nd season maize area			-12.824			-2.937
			(53.364)			(12.415)
Observations	353	309	353	353	309	353
F-test of instruments (GE soy)	6.35	13.70	22.58	6.35	13.70	22.58
F-test of instruments (2nd maize)	5.11	3.37	42.70	5.11	3.37	42.70
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Changes for Agricultural Cover in both dependent and explanatory variables are calculated over the years 1996 and 2006. Changes for Transition Agriculture to Forest in dependent variables are calculated over the years 1995 and 2005. The unit of observation is the municipality. The control variable frontier is a dummy variable indicating whether a municipality experienced increase in used agricultural land between 1996 and 2006. The variable initial forest is calculated as the total area covered with forest in 1991. Robust standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.